“*CRYPTOCURRENCIES AND THE GLOBAL FINANCIAL SYSTEM: RISK MANAGEMENT AND REGULATORY CHALLENGES IN FINANCIAL INSTITUTIONS*”

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I hereby declare that the work submitted is mine and that where I have made use of another's work, I have attributed the source(s) according to the Regulations set in the Student's Handbook.

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Abstract

This Dissertation Thesis was written as part of the M.Sc. in Banking & Finance, at the International Hellenic University ("IHU" thereafter).

Cryptocurrencies, or plainly stated hereof as "Cryptos", have always been at the center of attention for numerous institutional and individual investors, since their inceptions and categorization as digital currencies. Nowadays, cryptocurrencies market is mostly like a global hotspot. Albeit, they have recently been regulated by numerous financial institutions worldwide. The global regulatory framework imposed by banks, classified them as unique digital currencies or digital currency schemes. Moreover, their lucrative returns are extremely high and volatile compared to the ones of major global stock indices and gold. Our sample comprises of three of the oldest cryptocurrencies: Bitcoin, XRP and Litecoin, totaling a 70% market share. We include observations from the period from October 1, 2013 till October 1, 2020 and we treat them as our dependent variables. Our explanatory variables are of the same period of examination and consist of six global stock indices, being: S&P 500 (United States of America, U.S.A.), FTSE 100 (United Kingdom, U.K.), S&P/ASX 200 (Australia), STOXX50E (Europe), Nikkei 225 (Japan), HSI (Hang Sheng Index, Hong Kong) and the commodity of gold. By applying a General AutoRegressive Conditional Heteroskedasticity ("GARCH"), we analyze the total risk and the relationship between the returns' volatility of the three cryptocurrencies and the influence of returns of the six stock indices and gold upon them. Our results are adequately backed by prior research that indicates cryptocurrencies, in their vast majority, are not strongly interrelated with the stock markets and gold, even after the force-majeure strike of the newly pandemic COVID-19. Therefore, they are located somewhere in between, creating a new, unique asset class, a new investment opportunity.

Keywords: Cryptocurrencies, Return Volatility, Risk, Stock Indices, Gold, Regulatory Framework, Banks

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1. Introduction

To begin with, the world of cryptocurrencies, was created not more than ten years ago. They are digital currencies that operate via cryptographic procedures and secure financial transactions globally. They implement these financial transactions by incorporating the ground-breaking peer-to-peer electronic cash exchange that takes place directly and, of course, without any procrastinations and demands no more the presence of a financial intermediary. Previously, all transactions used to be utilized by the trustworthy third parties, mostly be the financial institutions that were playing the role of protecting the processes of the electronic payments. The strict and monopolistic presence of banks to monitor and secure the global electronic transactions has created mediation costs and, thereafter, has limited the transaction size and deteriorated the odds of a small casual transaction to be occurred. cryptocurrencies were created to overcome this “intermediation” burden and bring together a two-party transaction that could be executed instantly, or within a few minutes, without the intervention of a trusted third party (Nakamoto, 2008, Bitcoin.org).

Moreover, a plethora of cryptocurrencies are utilizing the so called blockchain technology to secure those financial transactions. However, it is beyond the purpose of this Thesis to shed light on such in-depth analysis of the blockchain technology applied. According to Frankenfield (Investopedia, 2020), cryptocurrencies are virtual currencies that apply cryptographical security and are almost improbable to be hacked or counterfeited. They operate in a total decentralized way and, therefore, this newly decentralized path grants them the advantage of existing and being transacted without the strict control of the governmental or third-party authorities.

Lee, Guo, and Wang (2018) stated that the invention of the very first cryptocurrency pseudonymously named Bitcoin (“BTC”) created a huge future wave of new numerous digital currencies, called altcoins. Almost all the emerged altcoins are a blend of cryptographic technology along with various algorithmic structures. A fruitful era came right after the first trading year in which the BTC had started raising its popularity with significantly large numbers in terms of volume and market capitalization. At this point is crucial to note that throughout this Thesis, we are going to analyze how the three of the oldest cryptocurrencies are operating, as far as their returns are concerned, and their potential threat to the traditional-fiat currencies and to the global financial economy. These three cryptocurrencies which will be scrutinizing are: i) Bitcoin (“BTC”), ii) Ripple’s XRP (“XRP) and iii) Litecoin (“LTC”). These three assets have always been on the top ten of the cryptocurrencies overall.

According to the database of the CoinMarketCap, currently (January 5th, 2021), the vast number of 8,188 cryptocurrencies are being traded worldwide with a combined market capitalization of a whopping $918.4 billion and hitting a 24-hour volume of $142.1 billion. With respect to our analysis we will engage in analyzing the three aforementioned cryptocurrencies. The dominant one is the BTC with a market share of 68.7%, market capitalization of $628.2 billion and with a price of $33,653.2 per BTC. XRP with the market capitalization of $10.2 billion, holds a market share of 1.11%. Its price is close to $0.227 per XRP. Last but not least, comes the LTC with a market capitalization of $10.255 billion, price $154.8 per LTC and market share of 1.14%.

Regarding the Regulatory Framework Challenges, it is noteworthy to mention that the substantially increased use of the cryptocurrencies the recent years raised concerns to a plethora of institutions on a global level. The peer-to-peer transactions could potentially range from simple individual transactions to huge intercontinental illegal financial transactions, possibly used for money laundering for instance. That is something that had to be somehow tracked and monitored in order for the respective governments to restrict illegal actions. According to a European Parliament paper’s atuthors Houben and Snyers (2018, 2020), even nowadays, cryptocurrencies are challenging and still pose a threat to the European Banks, since terrorism financing and money laundering cannot be traced through their networks and, thus, a regulatory arbitrage occurs. To avoid or, at least, mitigate this problematic approach, European Union Member States should create and strictly impose every new rule that Financial Action Task Force will set to clarify how the applications of the virtual assets should be incorporated smoothly across the EU. Some other examples are briefly mentioned below and more will be further outlined in chapter 2.

Another case within the EU central banks is described by Nabilou and Prüm (2019), categorizing the threats of cryptocurrencies to the banks in direct and indirect ones. The direct have strong influence on monetary policy, price stability and the right of the banks to create money. On the contrary, indirect threats refer to the considerable big gap between the banking systems and payment systems via cryptocurrencies. This gap is exactly where crucial risks lurk.

World Bank (2018) clearly states that are few issues turn up regarding the incorporation of cryptocurrencies into the traditional banking systems as there is still no “right and safe” trajectory that an individual bank can follow. The main reason is again the luck of strict regulatory framework that could be integrated throughout a financial transaction of a digital currency or a smart contract. First on the priority list for the World Bank will be the client protection.

As for our risk management theoretical part, the primary objective of this Thesis is to analyze the relationship of 3 major cryptocurrencies with six of the most powerful stock indices and gold, resulting in the general idea of being a new separate investment opportunity. Not much research has been done so far. On the top of that, most of the empirical results presented herein converge to the same outcome. Cryptocurrencies are affected little or not at all by other traditional assets like stocks, bonds, fiat currencies and commodities. Few cases are briefly introduced below and more will be further outlined in chapter 2.

Chaim and Laurini (2018) claimed that when cryptocurrencies, as assets, are compared to traditional financial assets like stocks, the outcome becomes a point of interest, since the existence of high levels of unconditional volatility, and large occasional price swings are occurring through their analysis.

Liu and Tsyvinski (2018) discovered that cryptocurrencies returns are not affected by the returns of fiat currencies and commodities. Akyildirima, Corbet, Luceye, Sensoy and Yarovaya (2019), by implementing the GARCH (1,1) methodology, explained that 22 major cryptos, by market cap and liquidity, are positively correlated with the volatility indices of the U.S.A. and Europe (VIX and VSTOXX, respectively), in times of global stock market turbulence and, therefore, present insignificant diversification for potential portfolio investments.

From the perspective of fiat currencies, Li and Huang (2020), examined the interconnection of BTC, XRP and LTC with gold and silver, major currencies and securities. Main outcome of their paper was that cryptocurrencies present a different risk source from that of the aforementioned traditional assets. The volatility spillovers among cryptos and these assets are “comparable in magnitude but “complementary” in trends”. Also, the introduction of the digital currencies to the already existing global traditional financial markets could potentially increase the systemic risk, if the latter’s risk is lesser.

Lastly, Corbet, Meegan, Larkin, Lucey and Yarovaya (2018) examined once again the connectedness between the 3 major cryptos and with other assets examined: MSC GSCI Total Returns Index, the USD Broad Exchange Rate, the S&P 500, gold, VIX and the Markit ITTR 110 Index. By implementing the generalized variance decomposition methodology (Diebold and Yilmaz, 2012), which is also presented in a plethora of research papers (e.g. Antonakakis et al., 2013, Batten et al., 2014 and Yarovaya et al., 2016), they extracted results similar to our expectations; interconnections amongst cryptos and no connection with the assets that are mainstream-used. Nonetheless, they do find similar behavioral patterns with those of the traditional assets, leading them to support that cryptos are constituting a new investment opportunity.

Lastly, it is noteworthy to mention that this Thesis is divided into two segments; in the first one, second chapter, we try to cover the theoretical background of how various financial institutions, worldwide, reacted to the existence and integration of the cryptocurrencies into the global economy by structuring rather lenient regulatory frameworks at first place, but as years passed, those restrictions have become more solid and accurate for tracking and monitoring instant cross-border transactions, without intermediaries, something crucial that banks have never taken into serious consideration in the near past. In addition, new innovative regulatory frameworks are still under development or they have already proposed by big financial institutions such as the European Central Bank ("ECB"), the International Monetary Fund ("IMF") and the Bank of International Settlements and the World Bank ("BIS"), in order to monitor and control the overwhelming and partly regulated power of the cryptocurrency and make looser the entrance hereof to the financial markets and converge their use with that of the fiat currencies. In the second segment, we also dive in the prior literature (also second chapter), as far as the relationship of the cryptocurrencies with the global financial ecosystem is concerned. A risk management approach indicates whether the digital assets standalone are affected or not by the traditional financial markets. Thereafter, in the third chapter, we present our data and methodology utilized for the outcome of this research. Moving on, we discuss the empirical findings and the results of the analyses outlined in the fourth chapter. Lastly, in the fifth chapter, conclusions are stated, along with the research limitations, based on our findings. The research is devoted to answer the question; "Can cryptocurrencies be diversified from the traditional financial assets?".

2. Literature Review

I. Banks Regulatory Framework Challenges

Although a plethora of digital coins were created a few years ago, their potential uses and advantages started to being utilized the three last years. Many a multinational corporation has started to using cryptocurrencies to execute fast electronic transactions, without the presence of an intermediary party (i.e., banks and other financial institutions). Using such uninvestigated and unregulated methods to proceed in financial transactions, posed substantial threats to the global financial ecosystem, because of the fact that these transactions may satisfy illegal actions like anti-money laundering, terrorism financing etc. Inevitably, this draw the attention of big systemic and central banks that tried to put an end in those illegal activities. Therefore, a majority of big banks worldwide, created regulatory frameworks to monitor these transactions and make their ambiguous procedures more transparent. Various banks so far, have also put limits in the amount of transactions made and minimized the leaks created by using cryptos as a parallel ecosystem. All in all, the above facts comprise the challenges that have to be taken by central banks in order to control the skyrocketing power of cryptocurrencies.

According to Olmos (2020) cryptocurrencies are named “People’s Money” or “Money 2.0” and referred as the leap, or evolution, of the traditional economic systems to the new digitalized reality. A new virtual, decentralized and denationalized system, that is globally accepted and backed by the transparent, but at the same time complex, blockchain technology, which, in turn, is reliable and open, has the potential of an ongoing evolution. The payments utilized via the cryptocurrencies, can enjoy a bunch of benefits in contrast with the traditional way of paying. The anonymity, privacy and the absence of third parties and governmental authorities are only a few of them. Their price is only affected by the powers of the global supply and demand; thus, they are not easily manipulated. This new reality of sending, receiving or storing electronic value however, does not comply with the traditional way of how central banks operate until nowadays and how they control and monitor money markets. Instead of integrating such indicatives, banks will more likely tend to regulate them, for the sake of money monitoring and centralization. Cryptocurrencies are now the best tool for groundbreaking solutions, with less bureaucratic processes, more protection and privacy. The challenge is: can banks alter their philosophy and operations to the new circumstances or extinct in the years ahead?

A very recent study, conducted by the European Parliament, regarding the regulatory challenges, has been addressed by Houben and Snyers (2020), who state that according to the European Union financial laws, any financial institution can use or store value of cryptocurrencies, albeit that could be a risky move, since these assets are, still, experiencing high volatilities in times of market turmoil and, therefore, banks could lose substantial amounts of money value, reflected in their balance-sheets. On the top of that, banks that have acquired cryptos, can, also, potentially exhibit a distorted financial image and root of this are the above reasons.

Challenges have also been recently identified from the International Monetary Fund (“IMF”) by Cuervo, Morozova, and Sugimoto (2019). The IMF states that, although a plethora of central banks worldwide and Anti-Money Laundering (“AML) / Combating the Financing of Terrorism (“CFT”) authorities have tried from the very beginning of the cryptos’ existence to put strictly limitations, many regulatory leaks are still present. The number of Initial Coin Offerings (“ICO”) has skyrocketed over the last 3 years and this triggered securities regulators to invent event stricter regulatory guidelines to monitor them or even ban them. Financial institutions in more than 80 countries have warned their clients and public about the functions of cryptocurrencies and few of them posted warnings regarding the ICOs. Official documents have been published by many jurisdictions about the lurking risks of cryptos. Other steps to combat those regulatory challenges include guidance on treatment of the uncertainty of digital assets and tailored and enforced regulation. The Financial Stability Board ("FSB") introduced "Decentralized financial technologies" (2019), which states how these new technologies (e.g. crypto trading platforms and peer-to-peer electronic transactions) should be taken into strong consideration for the regulatory bodies globally.

According to the Basel's Committee on Banking Supervision ("BCBS", 2019), its document published via The Bank for International Settlements ("BIS"), made clear for all the banking institutions that the utilization of cryptocurrencies as a medium of exchange or as electronic value storage, is a highly risky investment, since it does not follow the general guidance of how money is created, distributed and backed by governmental regulatory authorities. Instead, they are totally free, partly regulated, with considerably high volatility, exposing this way banks to a wide range of risks such as credit, liquidity and market risk, ML and CFT. In addition, BCBS warns that any financial institution that desires to integrate crypto-asset operations has to incorporate the following trajectories: i) due diligence, ii) adequate governmental and risk management approaches, iii) disclosure procedures and iv) provide adequate information to their supervisory authorities. Moreover, on its very last paper about "Designing a prudential treatment for crypto-assets" (2019), BCBS tries to shed light on the cryptos' use by introducing direct and indirect initiatives that could somehow measure the banks' potential exposure by including them into their operations.

The World Bank (2018), outlined the widespread use of cryptocurrencies and their blockchain technologies worldwide and especially in Europe and Asia. Also, stresses the fact that a massive number of financial institutions has already started incorporating a new era of fast electronic payment systems and new linkages with crypto wallets. Not all of them were a success though. This way World Bank indicates that with cryptos there will be neither banknotes nor coins and cryptos are going to amend the traditional banking operations in the way we know them. Central banks will not have the control of money. Individuals will have the power instead. This will, consequently, lead to a creation of digital markets that will replace the old traditional ones that utilized intermediaries for securing transactions. From the perspective of policy and regulation makers, there are three major challenges that have to be tackled: i) Taxation cannot completely keep up with the current laws regarding the electronic payments via cryptos. The markets still see cryptos as commodities rather than payment systems. ii) Should cryptocurrencies be banned or supported? iii) How should the regulatory authorities themselves can integrate and use cryptos for their own benefits and growth? Of course, the answers to the aforementioned challenges are yet to be discovered, since cryptos and blockchain technologies are still characterized by instability and uncertainty.

As far as Europe and European Central Bank ("ECB") are concerned, Nabilou and Prüm (2019) investigated whether the cryptocurrencies can affect, directly or indirectly, all the entities that are under the ECB's regulatory authority and how these challenges can be battled. Direct effects contain all the risks regarding prices' large fluctuations, which in turn affects the whole EU monetary policy, whereas the indirect effects concern the huge gaps between the traditional and cryptocurrency payment systems, under ECB's regulatory authority. In the paper two prospective solutions are presented: direct and indirect supervisory, oversight and regulatory measures. Direct measures address the formulation of strict regulatory guidelines, with which ECB can directly control the crypto market within the EU. Indirect measures require supervisory trajectories against the credentials used for accessing the cryptocurrency payment systems.

Auer and Claessens (2018) also state in their paper three key challenges stemming from the massive use of cryptos worldwide: i) The clarification of all the digital assets operations from the point of view of legal authorities and securities markets. ii) The identification of cross-border spillovers that come from the leakages of cryptos' use in unregulated activities such as ML and CFT. iii) Lastly, they stressed the fact that all the activities derived from the use of cryptos (i.e., cryptocurrency funds and products) can add a substantial dynamic in the current traditional financial system, hence new paths will be created. This, however, is not going to be a viable solution, since, nowadays, the crypto market is not characterized by stability, but at the same time, fortunately, they do have an insignificant impact to the global financial stability risk.

II. Risk Management, Return Volatility and the Relationship Between Cryptocurrencies And Other Financial Assets

The paper's main econometric analysis stems from the need of understanding whether cryptocurrencies are related with many other traditional financial assets. Not much prior research has been done so far, yet most of papers published are referred to the aforementioned query.

According to Dyhrberg's (2016a) paper, by applying a GARCH (1,1) and Exponential models with integrated AR(1,2) processes, analyzed whether BTC has similarities with gold and the fiat currency of dollar. The analyses showed that there are similarities with both the currency and the gold. Although, BTC is indeed a partly regulated digital currency as mentioned before, it is affected significantly by the federal funds rate and it also reacts symmetrically with gold, regarding the positive and negative shocks / good and bad news (Liu and Serletis, 2019). Therefore, it can be classified between gold and dollar and can be used in a portfolio of a risk averse investor, since it holds hedging capabilities in times of market uncertainty. In a later paper, Dyhrberg (2016b) analyzed also the hedging capabilities of BTC against the FTSE Index and the American dollar. The results indicated that, again, that BTC presented hedging capabilities against both of the two other instruments and can be introduced for a market portfolio analysis for minimizing the overall risk of a portfolio.

Akyildirim et al. (2019), implemented also a GARCH (1,1) methodology and scrutinized the relationship between 22 major (large capitalization) cryptocurrencies and two volatility indices, belonging to the U.S.A. and E.U. (VIX and VSTOXX, respectively). The results were slightly contradicting to the prior literature, as they found positive correlation amongst the two financial assets in times of market stress. Thus, they present insignificant diversification in an investment portfolio.

Corbet et al. (2017) checked the relationship between the return volatility of BTC with the returns of a big basket of various traditional financial assets (indices, currencies and commodities) when monetary policy decisions are announced by the jurisdictions of four central banks (Federal Open Market Committee of the U.S. central banks, ECB, Bank of England and Bank of Japan). Using OLS and GARCH (1,1) models, they concluded that cryptos, even though are affected by policy announcements, are not interrelated with the other assets. The surprising fact is that policy announcements are impacting the cryptos, although they are decentralized. Their results, though, are converged with Dyhrberg's (2016a, 2016b) that cryptos are the new asset class. Moreover, Corbet et al. (2018) explored the relationship of BTC, LTC and XRP with the explanatory variables of MSC GSCI Total Returns Index, the USD Broad Exchange Rate, the S&P500, gold, VIX and the Markit ITTR 110 Index. They founded interconnectedness between the three digital coins, whereas relatively low to no connection with the other financial assets and reported low, but significant idiosyncratic risk within the crypto market.

Ghorbel and Jeribi (2020) investigated five major cryptocurrencies' (BTC, XRP, Dash, Ethereum and Monero) relationship with the American indices of S&P 500, Nasdaq and VIX, gold and oil. The implementation of the multivariate BEKK-GARCH (1,1) methodology showed high volatility spillovers among cryptos and lower between the cryptos and the above-mentioned assets. Also, by computing the dynamic conditional correlations, they detected hedging capabilities of gold and BTC, especially for the U.S.A. investors, during stability periods in the markets, at least until the start of the COVID-19 pandemic.

Another paper for testing the risk and return tradeoff of three major cryptos (BTC, XRP and Ethereum) and stock, fiat currencies and commodities is published by Liu and Tsyvinski (2018). These three digital currencies are found to be not affected by the returns of the referred traditional assets and they do have little to no exposure to currencies and the commodities of gold, silver and oil. The study also reveals the fact that returns of cryptos can be predicted by two specific factors to their markets; momentum effect and investors' attention. Similar output is extracted from the paper of Malladi and Dheeriya (2020). They engaged Autoregressive-moving-average model with exogenous inputs model (ARMAX), GARCH and Vector AutoRegression (VAR) model and Granger Causality test to investigate the connection of returns and volatilities of BTC, XRP, stock indices and commodities. The results indicated that the returns of global stock market indices and gold do not affect the return volatility of the BTC, yet the returns of the XRP do affect the prices of BTC.

Sajter (2019) also examined whether the returns of BTC, XRP and Ethereum are affected by the returns of six major global stock indices; the S&P 500, Russell 2000 for the American stock market, the STOXX 600 for the E.U., the Nikkei 225 for the Japanese stock market, the HSI for the Chinese stock market and S&P Global 1200 for a global benchmark. After applying OLS models in the returns of all the assets, his study presented weakly relationship of the cryptos with the stock indices. Lastly, within the crypto market, BTC and Ethereum are interrelated, whereas the XRP is not related with either of them.

Lastly, Li and Huang (2020) examined the risk spillovers relationship among three cryptocurrencies (BTC, LTC and XRP) and the commodities of gold and silver along with the exchange rates of major currencies worldwide. Their paper underlines that cryptos contain a separate risk resource from this of the traditional assets. Therefore, the regulation of the illegal utilization of cryptos lies upon the lurking risk characteristics the latter, because it is still in a premature stage. Also, the volatility spillovers amongst the cryptos and the traditional assets can be put in comparison in terms of magnitude, yet they do present complementarity in trends. The last output of their paper is the fact that the incorporation of the crypto market can substantially increase the systematic risk of the existing traditional markets and their idiosyncratic risk can considerably impact the older markets, whenever times of uncertainty exist.

Finally, by taking into strong consideration all the prior literature mentioned before, we construct a new set of variables to explore. In few papers, BTC, as a standalone currency, has been investigated to reflect all cryptos behavior. In our converged case, we insert two more coins; XRP and LTC, that had significantly raised their market capitalization over the last year. We, also, introduce the returns of all major global stock indices and gold that could potentially impact the return volatility of the three cryptos and also analyze them from the overall risk exposure perspective.

3. Data & Methodology

In this chapter we are going to present all the methods and data utilized, to produce the outcome of the research. We primarily focus on three cryptos; BTC (Bitcoin), XRP (Ripple) and LTC (Litecoin). These digital assets have always been on the top ten ranking of all the existing cryptocurrencies, based on their market capitalization ($ 628.2, 10.2 and 10.3 billion respectively, as of January 5th, 2021, CoinMarketCap). We apply their returns as our dependent variables that will be examined, as well as examined by many other papers (e.g. Dyhrberg, 2016a, 2015b, Elsayed et al., 2020, Li and Huang, 2020, Corbet et al., 2018, Corbet et al., 2017). The analysis was estimated by using a sample of the daily closing prices, ranging from October 1st, 2013 to October 1st, 2020 (1,827 observations). The raw data (closing prices) of the cryptos was sourced from the CoinMarketCap (Cryptocurrency Prices, Charts And Market Capitalizations | CoinMarketCap). The most important reasons for choosing these three specific cryptos are their historical data availability and the fact that they are indeed the most popular and examined digital assets within the relative literature of the crypto market.

On the other hand, we want to include the return effects of the most influential global stock markets. To achieve that, we are incorporating in our research six major international stock indices. Moreover, we want to examine whether the hedging activity of the aforementioned cryptos is similar to that of the gold. The prime target is to examine the level of diversification of the digital currencies and these two traditional asset classes. Are the returns of the traditional financial assets affecting (and how) the return volatility of the cryptos? Can a potential investor include them in their portfolio? The six global stock indices' returns, used as our explanatory variables, are the following:

i) the S&P 500 Index (Accelerating Progress | S&P Global), for covering the 500 largest market cap entities that are listed in the stock exchanges across the U.S.,
ii) the STOXX50E Index, which contains the 50 "blue-chip" leading corporations that belong to eight countries of the Eurozone (Indices - Qontigo),
iii) the FTSE 100 Index (Financial Times Stock Exchange 100 Index, FTSE 100 Market overview | Hargreaves Lansdown (hl.co.uk)), representing the 100 largest U.K. companies by market capitalization,
iv) the S&P/ASX 200 Index [S&P/ASX 200 - S&P Dow Jones Indices (spglobal.com)], comprising also from the 200 largest companies by float-adjusted market capitalization, nested in the Australia,
v) the HIS Index (Hang Sheng Index, Hang Seng Indexes (hsi.com.hk)), which demonstrates the reefloat-adjusted market-capitalization-weighted stock-market index for the stock performance in the Hong Kong, and
vi) the Nikkei 225 (Nikkei Indexes), which is stock market index for the Tokyo Stock Exchange ("TSE"), comprising of the largest 225 corporations by market capitalization and they are nested in Japan.

Last but not least, our last explanatory variable is gold closing prices, sourced from the Federal Reserve Bank of St. Louis [(Federal Reserve Bank of St. Louis | Economic Data, Monetary Rates, Economic Education (stlouisfed.org)]. Closing prices for S&P 500, STOXXE50, S&P/ASX 200 and HIS were obtained from the yahoo!finance (https://finance.yahoo.com/), while closing prices for FTSE 100 and Nikkei 225 were extracted from the S&P Capital IQ (S&P Capital IQ Platform | S&P Global Market Intelligence). All variables' prices used are quoted against the U.S. dollar. In addition, because of the fact that cryptocurrencies are traded 365 days per year and our examined independent variables are traded 5 days per week, we restricted our sample to 1827 observations (excluded all the Weekends) and, thus including only the 5-day trading week, in order to unify harmonically all the data. The most crucial reason for choosing these specific variables in our research is that we want to scrutinize whether digital currencies are affected or not by these two totally different traditional asset classes.

Starting with our implemented methodology, we firstly compute the daily returns, R_t, of the cryptocurrencies, indexes and gold, which are obtained from the formula (1) below:

(1) $R_t = lnP_t - lnP_{t-1}$,

where R_t is the return of the asset at time t, lnP_t is the natural logarithm of the closing price of the asset at time t and lnP_{t-1} is the natural logarithm of the closing price of the asset at time t-1 (the previous day).

In **Figure 1** and **Figure 2** we can observe the historical daily dollar prices and the daily returns, respectively, of the three digital assets and our explanatory variables. As it can be seen from the **Figure 1**, all three cryptos present big price swings, with their peak in the late 2017 (December), as the majority of the existing cryptos that time had skyrocketed unexpectedly. It is worth mentioning that they have a slight uptrend over the examined years, albeit following different patterns as time passes. Same applies for the indices and gold. Their movements are clearly demonstrating non-stationary, like Dyhrberg (2016a) also highlighted. External market shocks have influence on all our variables. On the top of that, indices were heavily affected by the newly pandemic COVID-19, which had, and still has, catastrophic consequences. In March 2020 that COVID-19 stroke, the digital currencies showed no or little volatility in their prices. Same goes for the commodity of gold, which was affected, but fastly recovered and kept its uptrend. In addition, all stock indices but S&P 500, had also a speedy recovery in the wake of 2020.

Regarding the **Figure 2**, we are seeing periods of very high volatility and periods with a rather unexpected tranquility. The graphs are indeed stationary, since we are observing the first differences of the logged prices, returns, as we applied stationarity test and unit root was appeared. Stationarity is an important concept in our time series analysis and explains that the statistical properties of our research's time series do not change over time. The early and pioneering work on testing for a unit root in time series was done by Dickey and Fuller. Dickey-Fuller (DF) tests can be conducted allowing for an intercept, or an intercept and deterministic trend, or neither. The joint use of stationarity and unit root tests is known as confirmatory data analysis (Brooks, 2008), (*Notice: All tests used for our very last outcome of regressions are calculated with EViews 9*).

After, applying the Augmented Dickey-Fuller Test (ADF) both in the prices and in the returns, we found stationarity only in the first differences of the logged prices, returns, outlined in the **Table 1** and, therefore we continue all our research with the returns of our all variables. We implement the test in all three models; one with both intercept and trend, one with only intercept and one with neither of them. Results are all statistically significant at 1% and far below the indicative critical values (critical values at each level of significance are outlined in the appendix).

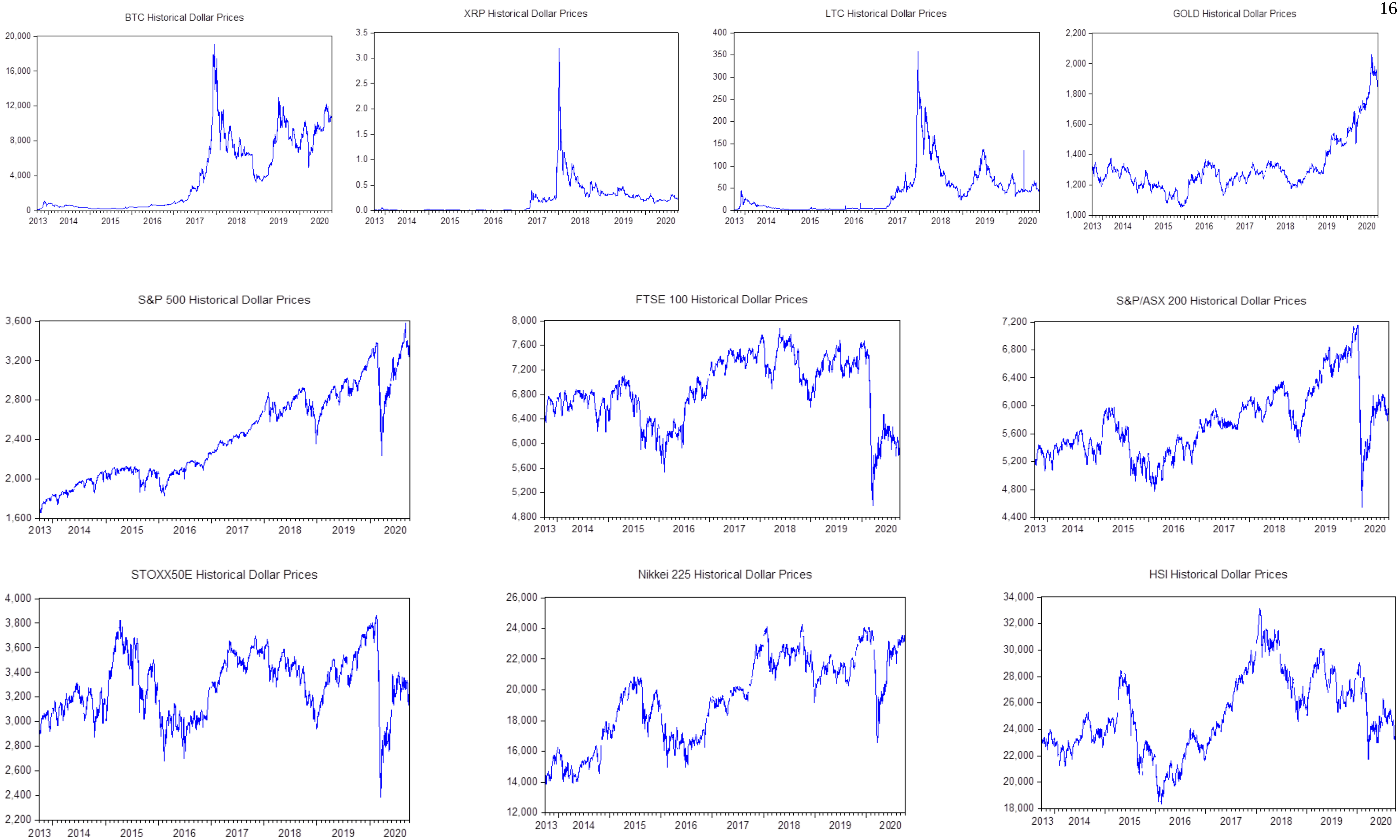

Figure 1. The levels of daily prices depicted for our dependent and explanatory variables, period October 1, 2013 – October 1, 2020.

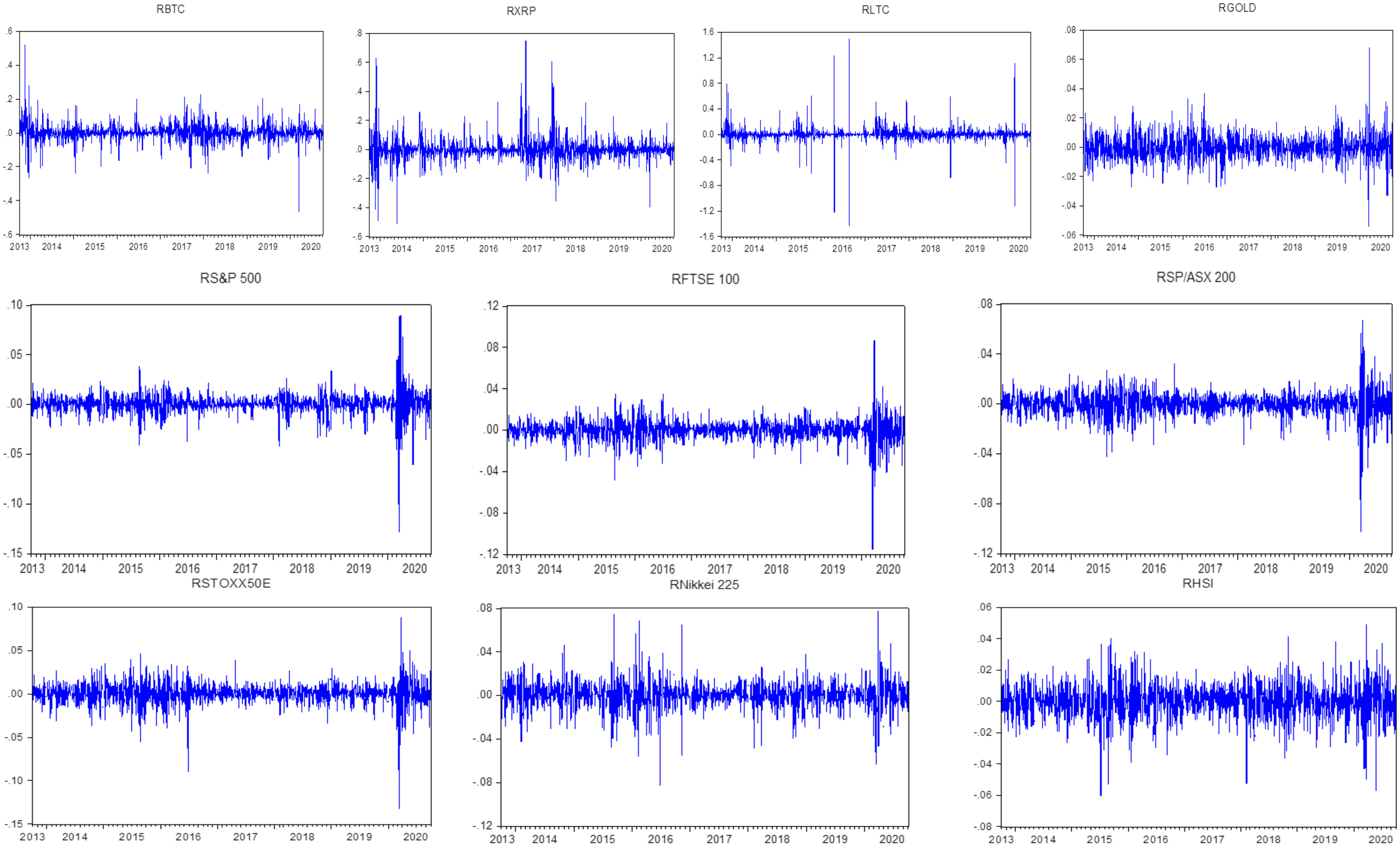

Figure 2. Daily returns depicted for our dependent and explanatory variables, period October 1, 2013 – October 1, 2020.

H$_0$: Variable has a unit root						
Variables	**Model 1**			**Model 2**		**Model 3**
	ADF	**Intercept**	**Trend**	**ADF**	**Intercept**	**ADF**
RBTC	-44.58859 (0.0000)***	1.742087 (0.0817)	-0.736296 (0.4616)	-22.98935 (0.0000)***	-0.055479 (0.9558)	-22.99563 (0.0000)***
RLTC	-55.74572 (0.0000)***	0.872013 (0.3833)	-0.508147 (0.6114)	-55.75480 (0.0001)***	0.864764 (0.3873)	-55.75197 (0.0001)***
RXRP	-26.80031 (0.0000)***	0.449823 (0.6529)	-0.049693 (0.9604)	-26.80761 (0.0000)***	0.815154 (0.4151)	-26.79768 (0.0000)***
RFTSE 100	-41.42469 (0.0000)***	0.806113 (0.4203)	-0.895595 (0.3706)	-41.41745 (0.0000)***	0.060559 (0.9517)	-41.43001 (0.0000)***
RS&P 500	-8.160266 (0.0000)***	0.672133 (0.5017)	-0.213039 (0.8313)	-8.178640 (0.0000)***	0.991939 (0.3215)	-8.146353 (0.0000)***
RS&P/ASX 200	-21.98294 (0.0000)***	0.577747 (0.5635)	-0.564765 (0.5723)	-21.98060 (0.0000)***	0.176996 (0.8595)	-21.98896 (0.0000)***
RSTOXX50E	-41.63738 (0.0000)***	0.826293 (0.4088)	-0.695605 (0.4868)	-41.63847 (0.0000)***	0.447949 (0.6542)	-41.64622 (0.0000)***
RNikkei 225	-18.53879 (0.0000)***	0.975185 (0.3296)	-0.819150 (0.4129)	-18.52302 (0.0000)***	0.532488 (0.5945)	-18.52328 (0.0000)***
RHSI	-40.38258 (0.0000)***	0.777644 (0.4369)	-0.616437 (0.5377)	-40.38586 (0.0000)***	0.487587 (0.6259)	-40.39476 (0.0000)***
RGOLD	-39.11075 (0.0000)***	-1.036405 (0.3002)	1.397925 (0.1623)	-39.07464 (0.0000)***	0.347789 (0.7280)	-39.08389 (0.0000)***

Table 1. ADF Tests's output. Probability reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

By taking a closer look to the summary statistics table, **Table 2**, we notice a few interesting key points to be investigated.

Descriptive statistics in returns										
Variables	**Mean**	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Obs.**	**Prob.**
RBTC	0.002401	0.001893	0.520791	-0.464730	0.049964	0.001615	17.35	15681.23	1827	0.00
RLTC	0.001616	0.000000	1.486931	-1.433727	0.109983	0.547491	70.36	345540.0	1827	0.00
RXRP	0.001707	-0.003282	0.750830	-0.512927	0.078604	1.605076	19.86	22434.24	1827	0.00
RFTSE 100	5.91e-06	0.000505	0.086668	-0.115124	0.010346	-1.041012	18.47	17557.36	1729	0.00
RS&P 500	0.000396	0.000643	0.089683	-0.127652	0.011193	-1.137606	26.07	38059.21	1699	0.00
RS&P/ASX 200	2.21e-05	0.000558	0.067665	-0.102030	0.010156	-1.228119	17.49	15580.78	1731	0.00
RSTOXX50E	0.000159	0.000518	0.088343	-0.132405	0.012494	-1.125036	16.05	12487.46	1708	0.00
RNikkei 225	0.000345	0.000696	0.077314	-0.082529	0.012827	-0.075710	8.61	2133.59	1624	0.00
RHSI	8.24e-05	0.000475	0.049250	-0.060183	0.011151	-0.353672	5.73	547.316	1650	0.00
RGOLD	6.86e-05	0.000000	0.067899	-0.054010	0.008446	0.213686	7.28	1329.29	1723	0.00

Table 2. Summary statistics of returns.

The table outlines both our dependent and independent variables and it clearly indicates that they are not normally distributed. This can be extracted from the Jarque-Bera Test, which shows that all returns' values are extremely higher than zero. Kurtosis of all the returns is also higher than the indicative number 3, as Kurtosis measures the tail behavior of each return distribution. All the sample's distributions are, therefore, leptokurtic. Regarding the measure of asymmetry, Skewness, we notice that the cryptos are slightly, positively skewed (bigger than the indicative number 0), meaning that an investor holding these assets can experience high gains when the market trend is upwards. Same applies for the commodity of gold as its Skewness is slightly above zero. On the contrary, all our remaining independent variables, which are the stock indices, present negative Skewness, meaning accordingly that if an investor holds them in their portfolio, they could potentially be benefited when the markets crash. The number of the observations is referring to the cryptos after deducting the Weekends from the sample, totaling 1,827, as also mentioned before. With respect to the explanatory variables, there are missing values due to various Official Holidays of each stock market across the globe. To fix that, an alignment was made in the raw data by filling the missing values with the average return of the previous and the next day, in the respective blanks. Apart from the Skewness numbers, it can also be seen from the table that wider fluctuations occur within the intervals of the three cryptos than in the range of those of the indices and gold. It is noteworthy to mention the fact that Litecoin has the wider intervals ranging from -143% to 149%, followed by XRP with a range between -51% and 75% and last comes BTC with narrower intervals from -46% to 52%. All indices and gold are not in parallel with cryptos, since their fluctuations are substantially smaller, with the gold holding an impressive pulsation of 10%. As for the standard deviation, once again cryptos demonstrate much higher than this of the indices. From the gold's perspective, standard deviation is pretty low measured at 0.8%.

After testing for unit roots and exploiting the advantage of stationarity and scrutinizing the descriptive statistics, we start by proposing an Ordinary Least Squares (OLS) regression to our analysis, by incorporating the log returns produced from the equation (1). Likewise, Sajter (2019) proposed an OLS model for examining the interconnectedness of the same three digital coins with the stock indices of the S&P 500, Russell 2000, Stoxx 600, Nikkei 225, HIS and S&P Global 1200. Linear approximations using the method of the OLS are applied to recognize which of our examined variables included in equation (1) are statistically significant and, as a consequence, may influence the returns of each cryptocurrency studied.

The OLS regression is estimated and the equation is the following:

(2) $Y_t = a_i + b_{it}X_t + u_t$,

where:

Y_t: is each one of our dependent variables at time t (RBTC, RLTC and RXRP)

X_t: is each one of the of the explanatory variables (stock indices and gold returns) at time t

a_i: constant term

b_{it}: the coefficient of its explanatory variable at time t

u_t: disturbance term at time t

Therefore, three different regression models incorporated as in below:

(3a) $RBTC_t = a_1 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + u_t$

(3b) $RLTC_t = a_2 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + u_t$

(3c) $RXRP_t = a_3 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + u_t$

Albeit implementing, at first the OLS model in our methodology, we had also to take into consideration tests concerning heteroskedasticity, autocorrelation and non-linearity. It is well known that if in the standard regression model, the error disturbances are heteroskedastic and / or autocorrelated, the least-squares regression coefficients are inefficient and the conventional estimator of their covariance matrix is usually inconsistent. The White variance-covariance matrix of the coefficients (i.e., the computation of the standard errors using the White correction for heteroscedasticity) is appropriate when the residuals of the estimated equation are heteroscedastic but serially uncorrelated. Most standard econometrics software packages have an option (usually called "Robust") that allows the user to employ standard error estimates that have been modified to account for the heteroscedasticity following White. The effect of using this correction is that, if the variance of the errors is positively related to the square of an explanatory variable, the standard errors for the slope coefficients are increased relative to the usual OLS standard errors, which would make hypothesis testing more "conservative", so that more evidence would be required against the null hypothesis before it would be rejected (Brooks, 2008).

Continuing, a test for determining whether AutoRegressive Conditional Heteroscedasticity effects (ARCH) are present in the residuals of an estimated model is made. The test is one of a joint null hypotheses that all q lags of the squared residuals have coefficient values that are not significantly different from zero. If the value of the test statistic is greater than the critical value from the χ^2 distribution, then, we reject the null hypothesis. This test can also be thought of as a test for autocorrelation in the squared residuals. Along with testing the residuals of an estimated model, the ARCH test is frequently applied to raw returns data (Brooks, 2008). Lastly, in our OLS models we find strong ARCH effects, by applying the ARCH test.

Moreover, in our three OLS models a general test for heteroskedasticity, White's test, was made, in order to double check the appropriateness for the first general regression proposed. This test looks for evidence of an association between the variance of the disturbance term and the regressors without assuming any specific relationship. For the Lagrange Multiplier (LM) test, if the Chi-Squared – Test Statistic is greater than the corresponding value from the statistical table then reject the null hypothesis that the errors are homoskedastic. In our case, the ARCH and White's tests outputs confirm the existence of heteroskedasticity, apart from the ARCH effects also mentioned in the above paragraph.

Therefore, it is also desirable to examine a joint test for autocorrelation that will allow the deeper examination of the relationship between u_t and several of its lagged values at the same time. The Breusch-Godfrey test is a more general test for checking whether there is autocorrelation or not. The Breusch–Godfrey test is a test that makes use of the u_t that are derived from the three aforementioned OLS regression analyses, and, thus, a test statistic is derived from these. The null hypothesis is that there is no serial correlation of any order up to p. Because of the fact that the test is also incorporated in the concept of Lagrange multiplier test, it is many a time referred to as the LM Test for serial correlation. If the test statistic exceeds the critical value from the Chi-squared statistical tables, we reject the null hypothesis of no autocorrelation. As with any joint test, only one part of the null hypothesis has to be rejected to lead to rejection of our hypothesis as a whole. So, the error at time t has to be significantly related only to one of its previous p values in the sample for the null of no autocorrelation to be rejected (Brooks, 2008). It is noteworthy that, when autocorrelation exists, then AutoRegressive (AR) models are estimated and also reflected within the three proposed OLS models, in order to refine them. As for the BTC no autocorrelation is detected. Regarding the other two cryptos, AR of order p up to 2 [AR(1) and AR(2)] processes were implemented, to repair the problem of autocorrelation (Dyhrberg, 2016a). Therefore, apart from the equation (3a), RLTC and RXRP OLS models are now restructured as:

(4a) $RLTC_t = a_4 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + b_{8t}RLTC(-1)_t + b_{9t}RLTC(-2)_t + u_t$

(4b) $RXRP_t = a_5 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + b_{8t}RXRP(-1)_t + b_{9t}RXRP(-2)_t + u_t$

Another evidence in addition, is that a Ramsey's Regression Equation Specification Error Test (RESET) test was made in the three OLS models. In particular, whether the model should be linear or not, can be formally tested using Ramsey's RESET test, which is a general test for misspecification of functional form. If the value of the test statistic is greater than the Chi-squared critical value, reject the null hypothesis that the functional form was correct. Consequently, the three models are proved to be mis-specified as we also supposed from the **Table 2**.

Finally, in the presence of heteroskedasticity, the OLS coefficients are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures are rather narrow. To overcome this weakness, along with all the diagnostic tests that we made previously regarding misspecification and autocorrelation, we therefore end up modeling variance volatility through Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models (Bollerslev, 1986) by assuming that the error term is not constant but varies over time. The best fitting GARCH (1,1), with reflected AR(1,2) processes for LTC and XRP within, models we are proposing for fixing all the issues detected above, are outlined with the mean equation (5a) and variance equation (5b) below:

(5a) $Y_t = a_i + b_{it}X_t + \varepsilon_t$, from which we derive the three models:

(5i) $RBTC_t = a_6 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + \varepsilon_t$

(5ii) $RLTC_t = a_7 + b_{1t}RFTSE100_t + b_{2t}RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + b_{8t}RLTC(-1)_t + b_{9t}RLTC(-2)_t + \varepsilon_t$

(5iii) $RXRP_t = a_8 + b_{1t}RFTSE100_t + b_2RGOLD_t + b_{3t}RHSI_t + b_{4t}RNikeei225_t + b_{5t}RS\&P500_t + b_{6t}RS\&P/ASX200_t + b_{7t}RSTOXX50E_t + b_{8t}RXRP(-1)_t + b_{9t}RXRP(-2)_t + \varepsilon_t$

(5b) $\sigma^2_t = a_0 + a_1u^2_{t-1} + \beta\sigma^2_{t-1}$, where:

Y_t: is one of our dependent variables at time t (RBTC, RLTC and RXRP)

X_t: is each one of the of the explanatory variables (stock indices and gold returns) at time t

a_i: constant term

b_{it}: the coefficient of its explanatory variable at time t

ε_t: disturbance term at time t

σ_t^2: is the conditional variance of ε_t in equations.

The conditional variance, σ_t^2, must be nonnegative and positive, hence, restrictions of $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta \geq 0$ are sufficient conditions to ensure $\sigma_t > 0$ (stability condition) and also the wide-sense stationarity condition, $\alpha_1 + \beta < 1$. The ARCH term, α_1, indicates the short run persistence of shocks, while the GARCH term, β, represents the contribution of shocks to long run persistence. From the perspective of the financial assets, we look closer at α_1 as the volatility clustering of the cryptos and β as the volatility dependence.

4. Empirical Results & Interpretations

I. Correlation Evidence

First and foremost, we want to examine whether our scrutinized financial assets' returns (both the cryptos, indices and gold) are mutually correlated and also test the strength of each relationship. In the **Table 3**, outlined below, we can observe these pairs that have high correlation, positive or even negative in the correlation matrix and those that are totally uncorrelated. The diagonal cells indicating the value of 1 show that each variable always perfectly correlates with itself. Below the correlation coefficient we can see the probabilities. To be more specific, it can be clearly noticed in the **Table 3** that almost all the correlated pairs do not raise a severe multicollinearity problem. Unsurprising, though, is the fact that most of the stock indices are mutually correlated, but they are all almost uncorrelated with cryptos. From the point of view of gold, we experience even negative correlations with the Japanese Stock Index, Nikkei 225, and the European Blue-Chips Index, STOXX50E, as these two regions traditionally do hold gold features in their portfolio as a more conservative approach because gold can pretty much indicate hedging activity, with regards to all volatile financial assets examined in here. Regarding the cryptos, BTC has moderate correlation with the remaining two, whereas the correlation becomes half of the aforementioned between XRP and LTC. Similarly, in Sajter's (2019) study, all the three digital currencies examined (Bitcoin, Ethereum and XRP), are mutually correlated, albeit weakly correlated or uncorrelated with most of the stock indices. Lastly, only one pair exceeds the 50% threshold by 2.59%, which in turn, cannot present significant multicollinearity evidence [(Grewal, Cote and Baumgartner (2004)].

Correlation Probability	RBTC	RLTC	RXRP	RFTSE 100	RGOLD	RHSI	RNikkei 225	RS&P 500	RS&P/ASX 200	RSTOXX 50E
RBTC	*1.000000* -----									
RLTC	*0.455976* *0.0000*	*1.000000* -----								
RXRP	*0.418292* *0.0000*	*0.274231* *0.0000*	*1.000000* -----							
RFTSE 100	*0.101908* *0.0000*	*0.072620* *0.0019*	*0.074920* *0.0014*	*1.000000* -----						
RGOLD	*0.054000* *0.0210*	*0.026445* *0.2586*	*0.043081* *0.0656*	*-0.010822* *0.6439*	*1.000000* -----					
RHSI	*0.010975* *0.6392*	*0.059255* *0.0113*	*0.026400* *0.2594*	*0.456439* *0.0000*	*0.003367* *0.8857*	*1.000000* -----				
RNikkei 225	*-0.005849* *0.8027*	*0.027244* *0.2445*	*0.008684* *0.7107*	*0.352963* *0.0000*	*-0.159493* *0.0000*	*0.489855* *0.0000*	*1.000000* -----			
RS&P 500	*0.117201* *0.0000*	*0.048754* *0.0372*	*0.096413* *0.0000*	*0.499851* *0.0000*	*0.042796* *0.0674*	*0.265454* *0.0000*	*0.220504* *0.0000*	*1.000000* -----		
RS&P/ASX 200	*0.082802* *0.0004*	*0.069979* *0.0028*	*0.039811* *0.0889*	*0.438918* *0.0000*	*-0.012127* *0.6045*	*0.462264* *0.0000*	*0.473216* *0.0000*	*0.369136* *0.0000*	*1.000000* -----	
RSTOXX50E	*0.093726* *0.0001*	*0.056750* *0.0153*	*0.062680* *0.0074*	*0.458994* *0.0000*	*-0.055396* *0.0179*	*0.435695* *0.0000*	*0.370624* *0.0000*	*0.525829* *0.0000*	*0.382942* *0.0000*	*1.000000* -----

Table 3. EViews Correlation Matrix / Included Observations: 1,827

II. The Ordinary Least Squares Regression Analyses

The results of the three OLS regressions are presented in the **Table 5** below and as it can be noticed that they are quantitatively similar to each other. The OLS regression models were utilized to examine the effect of every variable in each one of the baseline cryptocurrencies models. Firstly, after testing the stationarity of our financial time series we found that their returns are stationary and contain a unit root by applying the ADF test. Secondly, after testing the serial correlation with the Breusch–Godfrey test (**Table 4**), we discovered strong autocorrelation presence in the models of the two smaller capitalization cryptocurrencies and we corrected the models by applying AutoRegressive processes with an order of p = 2 [AR(2)]. As we can clearly see in **Table 5**, the outcomes of the models are in contrary with Sajter's (2019). We also conducted three more tests to completely verify that our firstly proposed OLS models are not appropriate for examining the interconnectedness between the three cryptocurrencies and the traditional financial assets. Our OLS models cannot interpret this interconnection, since pretty much no coefficient is statistically significant for the XRP and LTC and also, the R^2 are impressively low and, therefore, the models cannot explain the objective of the research.

By implementing the Ramsey's RESET test, we checked that the 3 models are not the best-fitted as it can bee seen in the **Table 6**. Finally, we applied two different tests of detecting heteroskedasticity and ARCH effects, the White's test and the ARCH test (**Table 7**). The reason behind using the White's test is that this specific test is the most powerful test regarding the detection of heteroskedasticity. From the other hand, ARCH tests were made in order to see if our OLS regressions do have ARCH effects.

Serial Correlation LM Test (Breusch-Godfrey)				
Values		**RBTC**	**RLTC**	**RXRP**
Without correction	F-Statistic	1.674359 (0.1877)	67.21279 (0.0000)***	15.15260 (0.0000)***
	LM (2-lag)	3.360953 (0.1863)	125.8544 (0.0000)***	29.97209 (0.0000)***
With correction	F-Statistic	-	0.699597 (0.4969)	1.312419 (0.2694)
	LM (2-lag)	-	1.407369 (0.4948)	2.638392 (0.2674)

Table 4. The results of the test in the OLS regressions show that after incorporating the AR(2) processes in RLTC and RXRP, we correct the problem of autocorrelation. Therefore, we cannot reject the null hypothesis of no autocorrelation. P-values in the parentheses are indicating insignificance of the test after the correction. No amendment for the BTC was made, since it had no signs of autocorrelation from the beginning. (Probability reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.)

	Dependent variable: RBTC			**Dependent variable: RLTC**			**Dependent variable: RXRP**		
Variables	***Coefficient***	***t-Statistic***	***Probability***	***Coefficient***	***t-Statistic***	***Probability***	***Coefficient***	***t-Statistic***	***Probability***
a	0.0023*	1.9287	0.0539	0.0016	0.8548	0.3927	0.0016	0.7143	0.4751
RFTSE 100	0.2239	0.8371	0.4026	0.4665	0.9551	0.3396	0.3619	0.9975	0.3186
RGOLD	0.2784*	1.7910	0.0735	0.2147	0.7358	0.4619	0.2540	1.1322	0.2577
RHSI	-0.2247	-1.2490	0.2118	0.1083	0.3803	0.7037	-0.0436	-0.2067	0.8363
RNikkei 225	-0.2014*	-1.6958	0.0901	-0.0167	-0.0655	0.9478	-0.1232	-0.6783	0.4977
RS&P 500	0.3122**	2.0787	0.0378	0.1624	0.5179	0.6046	0.5831***	2.7830	0.0054
RS&P/ASX 200	0.3713**	2.2448	0.0249	0.4066	1.2664	0.2055	0.1027	0.4648	0.6421
RSTOXX50E	0.1127	0.5398	0.5894	-0.1409	-0.3473	0.7284	-0.1334	-0.4450	0.6564
AR (1)				-0.2733***	-11.641	0.0000	0.1149***	4.9044	0.0000
AR (2)				-0.0647***	-2.7598	0.0058	0.0533**	2.2860	0.0224
R-squared		*0.023535*			*0.076886*			*0.028726*	
Log-Likelihood		*2904.358*			*1513.656*			*2086.860*	
F-Statistic		*6.263043*			*16.79681*			*5.964462*	
Prob (F-Statistic)		*0.000000*			*0.000000*			*0.000000*	
Akaike Info Criterion		*-3.170617*			*-1.647843*			*-2.276010*	
Schwarz Criterion		*-3.146488*			*-1.617655*			*-2.245822*	

Table 5. OLS Regressions for RBTC, RLTC and RXRP. (Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.)

Ramsey's RESET Test		
Models	**Values**	
RBTC	T-Statistic	4.763960 (0.0000)***
	F-Statistic	22.69532 (0.0000)***
	Likelihood Ratio	22.66648 (0.0000)***
RLTC	T-Statistic	12.34198 (0.0000)***
	F-Statistic	152.3244 (0.0000)***
	Likelihood Ratio	147.1528 (0.0000)***
RXRP	T-Statistic	2.452224 (0.0143)**
	F-Statistic	6.013403 (0.0143)**
	Likelihood Ratio	6.039862 (0.0140)**

Table 6. The results of Ramsey's RESET test in the OLS models indicate that the functional form is non-linearity in each model, because the value of the test statistic is greater than the χ^2 critical value and reject the null hypothesis that the functional form is correct. (Probability reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.)

Models	Values	ARCH Test	White Test
RBTC	F-Statistic	16.14743 (0.0000)***	5.955150 (0.0000)***
	LM	77.55588 (0.0000)***	190.4553 (0.0000)***
RLTC	F-Statistic	75.76298 (0.0000)***	7.904402 (0.0000)***
	LM	314.4101 (0.0000)***	354.5910 (0.0000)***
RXRP	F-Statistic	52.96557 (0.0000)***	5.409769 (0.0000)***
	LM	231.8550 (0.0000)***	258.5353 (0.0000)***

Table 7. Presents the results of heteroskedasticity tests (ARCH and White) in relation to the OLS regression in each cryptocurrency. The table indicates that there is heteroskedasticity in each OLS model, since as regards the LM test, the χ^2 – test statistic is greater than the corresponding value. So, we reject the null hypothesis that the errors are homoscedastic. (Probability reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.)

III. The GARCH Models Estimations

In the wake of implementing all these tests in our research, we confirmed that a conventional GARCH model can be used for the sake of our analyses (Bollerslev, 1986) with an AR(1,2) processes incorporated. Moreover, the models are found to be the most parsimonious, since they all hold the minimum Schwarz and Akaike Information Criteria. It can be seen that the best-fitted models to examine the relationship among the digital assets and the traditional financial assets by looking on return volatility and the conditional variance, as the total risk, of the 3 cryptocurrencies.

In the mean equations, unsurprisingly, we get the anticipated outcome. Return volatility of the two smaller capitalization coins points out that XRP and the LTC are pretty much not affected by almost all the included stock market indices, hence, they are pretty much unrelated and can be used as hedging-capable assets or medium exchange against these big-capitalization-fused stock indices and gold (Dyhrberg, 2016b, Cermak, 2017, etc). More specifically, the XRP is affected positively only by the returns of the U.S. stock market (S&P 500) and the gold. Their coefficients are weakly positive and statistically significant at 5% and 10%, respectively. Positive shocks from the S&P 500 influence XRP, since a plethora of U.S. companies that are components of the index, are starting to use it as a payment method. Regarding the LTC, its return volatility is affected positively only from the Europe stock market (STOXX50E) and its coefficient is significant also at 5%. As for the return volatility of the BTC, U.S. and Australian stock indices' returns do positively affect it, yet their significance is mediocre enough to indicate a substantial connection among them. From the flipside, Nikkei 225 coefficient is negative and decrease BTC's volatility. The U.K. and Hong Kong markets seem to be out of the game and it turns out to be that all three cryptocurrencies can have hedging capabilities and reversed influence against them. Dyhrberg (2016a, 2016b) states that Bitcoin, along with gold, can minimize, with their hedging abilities, market specific risks. As far as gold is concerned, we also observe weak influence on all three coins. Consequently, in all three digital coins, we mostly observe relatively low to no relationship with the stock indices and gold overall. That indicates the existence of a new asset class that is partially influenced by traditional financial assets, and is located somewhere in between the commodity of gold and the stock indices.

The most crucial point on the variance equations, though, lies in the conditional variances (σ^2) as they represent the total risk of the cryptocurrencies. Its decomposition in the idiosyncratic risk (volatility clustering: a_1 coefficient) and systematic risk (volatility dependence: β coefficient) are worth mentioning, since all the coefficients in our three models have strong statistical significance. From the total risk decomposition, we conclude that the biggest portion in each digital asset is explained from the systematic part (β coefficients for RBTC, RLTC and RXRP respectively: 0.82, 0.75 and 0.7), meaning that they might be possibly affected more significantly by big global / macroeconomic events. Idiosyncratic risk is present and statistically significant, but in much lesser extent (a_1 coefficients, respectively: 0.16, 0.12 and 0.26), meaning that digital coins' returns are not affected substantially by firm / country specific news, as far as our explanatory variables are concerned. Moreover, this low rate of the idiosyncratic component is, also, pretty much connected with their decentralized presence in the global markets. Albeit this seems rather low, yet in times of market uncertainty, cryptos' idiosyncratic risk may substantially increase the one of traditional markets, as introduced by Li and Huang, 2020. This outcome can lead us to reconfirm our first hypothesis. Cryptocurrencies are on the verge of the creation of a new asset class. Furthermore, their partial connectedness with the traditional financial markets can sometimes be even more insignificant in the wake of global macroeconomic, or even force-majeure events. On the other side of the coin, cryptocurrencies returns' volatility might converge with this of gold in such cases, which shows similar hedging capabilities with BTC and the other two coins (Dyhrberg, 2016a, 2016b). Characteristic example is the COVID-19 pandemic that came in early 2020 and crashed all markets globally, except for gold and cryptocurrencies that had barely been affected by the

	Dependent variable: RBTC			Dependent variable: RLTC			Dependent variable: RXRP		
Variables	***Coefficient***	***z-Statistic***	***Probability***	***Coefficient***	***z-Statistic***	***Probability***	***Coefficient***	***z-Statistic***	***Probability***
a	0.0010	1.0455	0.2958	0.0028	0.6920	0.4889	-0.0044***	-3.1014	0.0019
RFTSE 100	0.1682	0.9318	0.3514	-0.9118	-1.2252	0.2205	0.1839	0.8448	0.3982
RGOLD	0.1860*	1.6639	0.0961	0.6824*	1.6525	0.0762	0.3124*	1.6997	0.0558
RHSI	-0.0941	-0.8666	0.3861	-0.4945	-1.4218	0.1551	-0.0363	-0.2974	0.7661
RNikkei 225	-0.2279**	-2.3157	0.0206	-0.0653	-0.1901	0.8493	0.0294	0.2523	0.8008
RS&P 500	0.4271**	5.1516	0.0980	-0.2346	-0.4495	0.6531	0.7016**	5.7157	0.0661
RS&P/ASX 200	0.2854**	2.1572	0.0310	0.8181	1.4361	0.1510	0.0571	0.3819	0.7026
RSTOXX50E	-0.0942	-0.6208	0.5347	0.4624**	2.3590	0.0183	-0.1642	-0.8096	0.4182
AR (1)				-0.0830**	-2.0253	0.0428	0.0698**	2.4130	0.0158
AR (2)				-0.0011	-0.0449	0.9642	0.0030	0.1252	0.9003
Variance Regressors									
a_0	0.000110***	11.26964	0.0000	0.014429***	74.20330	0.0000	0.000362***	18.34397	0.0000
a_1	0.155297***	14.03738	0.0000	0.124495***	7.172495	0.0000	0.259125***	16.35273	0.0000
β	0.816675***	72.48580	0.0000	0.759890***	50.91287	0.0000	0.696214***	51.89889	0.0000
Akaike info criterion		-3.407249			-1.783526			-2.786299	
Schwarz criterion		-3.374072			-1.744316			-2.747090	

Table 8. GARCH (1,1) model estimations with dependent variables: RBTC, RLTC and RXRP. (Probability reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.)

pandemic, bounced back extremely quickly and gained upward momentum in the following months (**Figure 1**). To be more precise, apart from the U.S. stock index S&P 500, no other index indicated signs of fast recovery. Therefore, our research proved twice the diversification benefits that cryptocurrencies can offer for a potential investor. Firstly, their meager correlation, or even no correlation, with the most powerful global stock indices and gold, results in the fact that their return volatility cannot be substantially affected by the returns of those assets. Secondly, their hedging capabilities in unexpected market turbulences, like gold's, can persist, because of their positive indications of significant systematic risk. In a nutshell, crypto is neither gold nor stock. Is a new asset class – a new investment opportunity.

5. Conclusion & Recommendations

This paper reports the major regulatory framework challenges that financial institutions worldwide have to tackle in order to monitor and control the crypto market's operations and investigates the relationship between three of the top traded cryptocurrencies (BTC, LTC and XRP), by market capitalization, and six major stock indices along with gold. The main hypothesis is whether the digital coins' total risk and return volatilities are affected by the returns of the traditional financial assets, hence, creating a new asset class. The investigation of the hypothesis, only after implementing the GARCH (1,1) methodology, resulted in the fact that the returns of the stock indices and gold have little to no impact on all of the three cryptos. Moreover, we observe high significant systematic risk component of the total risk decomposition of the three digital assets and lower, but significant, idiosyncratic risk, meaning that they are affected in bigger magnitude by big macroeconomic events rather that firm / country specific ones. Also, during force majeure events, COVID-19 for instance, the cryptocurrencies showed similar hedging capabilities with the commodity of gold, followed by their significantly high systematic risk. Therefore, these digital assets have the potential to be a new asset class, since they can offer diversification prospects.

It is worth mentioning the limitation of the traditional assets being traded only in the weekdays, whereas cryptos are traded on daily basis. In addition, another limitation of this research is that we did not incorporate stable coins along with the three examined digital coins. The use of stable coins might have an overall reduction of their own risk resource, since a plethora of such coins have started to be issued by central banks and other financial institutions. That might also ameliorate the global regulatory frameworks implemented for the legal use of cryptocurrencies. Lastly, another interesting addendum for a potential investigation could be the relation between the big capitalization cryptocurrencies and the exchange rates of fiat currencies of the most powerful central banks worldwide. These kinds of studies will be useful for examining whether digital currencies can coexist with fiat currencies, even replacing them, as the new version of money.

Bibliography

- Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A. and Yarovaya, L. (2020) The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters* 33, 101212.
- Antonakakis, N. and Vergos, K. (2013) Sovereign bond yield spillovers in the euro zone during the financial and debt crisis. *J. Int. Finance. Mark. Inst. Money* 26(1), pp. 258–272.
- Auer, R. and Claessens, S. (2018) Regulating Cryptocurrencies: Assessing Market Reactions, *BIS Quarterly Review*. pp. 51-65.
- Basel Committee on Banking Supervision. (2019) Designing a prudential treatment for crypto-assets. Discussion paper. *Bank of International Settlements*. Available: https://www.bis.org/bcbs/publ/d490.pdf
- Basel Committee on Banking Supervision. (2019) Statement on crypto-assets. *Bank of International Settlements.* Available: Statement on crypto-assets (bis.org)
- Batten, J.A., Ciner, C. and Lucey, B.M. (2014) Which precious metals spill over on which, when and why? Some evidence. *Appl. Econ. Lett.* 22(6), pp. 466–473.
- Bernard, M. (2018) What Is The Difference Between Bitcoin And Ripple? *Forbes*. Available: https://www.forbes.com/sites/bernardmarr/2018/02/28/what-is-the-difference-between-bitcoin-and-ripple/?sh=75f127886611
- Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity. *J. Econom.* 31(3), pp. 307–327.
- Brooks, C. (2008) Introductory Econometrics for Finance. Second edition. *Cambridge: Cambridge University Press*.
- Cermak, V. (2017) Can Bitcoin Become a Viable Alternative to Fiat Currencies? An Empirical Analysis of Bitcoin's Volatility Based on a GARCH Model. *SSRN Electronic Journal*. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2961405
- Chaim, P. and Laurini M. P. (2018) Volatility and return jumps in bitcoin. *Economics Letters* 173, pp. 158–163.
- Chapelle, A. (2019) Operational Risk Management: Best Practices in the Financial Services Industry. First Edition. *New York: John Wiley & Sons Ltd.* Chapter 19, pp. 207–219.
- Corbet, S., McHugh, G. and Meegan, A. (2017) The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment Management and Financial Innovations* 14(4), pp. 60–72.
- Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018) Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economic Letters* 165, pp. 28–34.
- Cuervo, C., Morozova, A. and Sugimoto, N. (2019) Regulation of Crypto Assets. *International Monetary Fund*, Washington, DC. Available: Regulation of Crypto Assets (imf.org)
- D'Alfonso, A., Langer, P. and Vandelis, Z. (2016) The Future of Cryptocurrency. Working Paper. *Toronto: Ryerson University*.
- Demiralay, S. and Bayracı, S. (2020) Should stock investors include cryptocurrencies in their portfolios after all? Evidence from a conditional diversification benefits measure. *International Journal of Finance and Economics*, pp. 1–17.
- Diebold, F.X. and Yilmaz, K. (2012) Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1), pp. 57–66.
- Dyhrberg, A. H. (2016a) Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters* 16, pp. 85–92.
- Dyhrberg, A. H. (2016b) Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters* 16, pp. 139–144.

- Elsayed, A. H., Gozgor, G. and Lau, C. K. M. (2020) Causality and dynamic spillovers among cryptocurrencies and currency markets. *International Journal of Finance and Economics*, pp. 1– 15.
- Frankenfiled, J. (2020) What Is a Cryptocurrency? Investopedia. Available: https://www.investopedia.com/terms/c/cryptocurrency.asp
- Ghorbel, A. and Jeribi, A. (2021) Investigating the relationship between volatilities of cryptocurrencies and other financial assets. *Decisions in Economics and Finance*. Available: https://link.springer.com/article/10.1007/s10203-020-00312-9#citeas
- Grewal, R., Cote, J. A. and Baumgartner, H. (2004) Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing science* 23(4), pp. 519–529.
- Lee, D. K. C., Guo, L. and Wang, Y. (2018) Cryptocurrency: A New Investment Opportunity? *The Journal of Alternative Investments*, 20(3), pp. 16–40.
- Li, S. and Huang, Y. (2020) Do Cryptocurrencies Increase the Systemic Risk of the Global Financial Market? *China & World Economy*, 28(1), pp. 122–143.
- Liu, J. and Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review*, 30(4), pp. 779–811.
- Liu, Y. and Tsyvinski, A. (2018) Risks and returns of cryptocurrency, *National Bureau of Economic Research*. Working Paper 24877. Available: https://www.nber.org/papers/w24877
- Malladi, R.K. and Dheeriya, P.L. (2021) Time series analysis of Cryptocurrency returns and volatilities. *Journal of Economics and Finance* 45, pp. 75–94.
- Nabilou, H. and Prum, A. (2019) Central Banks and Regulation of Cryptocurrencies. Review of Banking and Financial Law (Forthcoming). *University of Luxembourg Law*. Working Paper No. 2019–014. Available: https://ssrn.com/abstract=3421417
- Nakamoto, S. (2008) Bitcoin: a peer-to-peer electronic cash system. Available: https://bitcoin.org/bitcoin.pdf
- Olmos, A. (2020) Will Central Banks Adopt the New World Economy of Cryptocurrencies? *The PayTech Book: The Payment Technology Handbook for Investors, Entrepreneurs and FinTech Visionaries*. pp. 119–121.
- Prof. Dr. Houben, R. and Snyers, A. (2020) Crypto-assets – Key developments, regulatory concerns and responses, Study for the Committee on Economic and Monetary Affairs, Policy Department for Economic, Scientific and Quality of Life Policies, *European Parliament*, Luxembourg. Available: http://www.europarl.europa.eu/supporting-analyses
- Sajter, D. (2019) Time-Series Analysis of the Most Common Cryptocurrencies. *Ekonomska misao i praksa*, 13(1), pp. 267–282.
- World Bank. (2018) Cryptocurrencies and Blockchain. Europe and Central Asia Economic Update (May), *Washington, DC: World Bank*. License: Creative Commons Attribution CC BY 3.0 IGO. Available: http://documents1.worldbank.org/curated/pt/293821525702130886/pdf/Cryptocurrencies-and-blockchain.pdf
- Yarovaya, L., Brzeszczyński, J. and Lau, C.K.M. (2016) Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *Int. Rev. Finance Anal.* 43, pp. 96–114.

Appendix

	Model 1		Model 2		Model 3	
Variables	**Critical values**		**Critical values**		**Critical values**	
RBTC	1%	-3.963076	1%	-3.433730	1%	-2.566229
	5%	-3.412271	5%	-2.862919	5%	-1.940997
	10%	-3.128067	10%	-2.567551	10%	-1.616583
RLTC	1%	-3.963076	1%	-3.433730	1%	-2.566229
	5%	-3.412271	5%	-2.862919	5%	-1.940997
	10%	-3.128067	10%	-2.567551	10%	-1.616583
RXRP	1%	-3.963079	1%	-3.433732	1%	-2.566230
	5%	-3.412273	5%	-2.862920	5%	-1.940997
	10%	-3.128068	10%	-2.567552	10%	-1.616583
RFTSE 100	1%	-3.963495	1%	-3.434025	1%	-2.566334
	5%	-3.412477	5%	-2.863050	5%	-1.941011
	10%	-3.128189	10%	-2.567621	10%	-1.616573
RS&P 500	1%	-3.967708	1%	-3.436991	1%	-2.567391
	5%	-3.414536	5%	-2.864361	5%	-1.941156
	10%	-3.129410	10%	-2.568324	10%	-1.616476
RS&P/ASX 200	1%	-3.963736	1%	-3.434194	1%	-2.566395
	5%	-3.412594	5%	-2.863125	5%	-1.941020
	10%	-3.128259	10%	-2.567661	10%	-1.616567
RSTOXX50E	1%	-3.963578	1%	-3.434083	1%	-2.566355
	5%	-3.412517	5%	-2.863076	5%	-1.941014
	10%	-3.128213	10%	-2.567635	10%	-1.616571
RNikkei 225	1%	-3.965066	1%	-3.435131	1%	-2.566728
	5%	-3.413245	5%	-2.863539	5%	-1.941065
	10%	-3.128645	10%	-2.567884	10%	-1.616537
RHSI	1%	-3.963881	1%	-3.434296	1%	-2.566431
	5%	-3.412665	5%	-2.863170	5%	-1.941025
	10%	-3.128301	10%	-2.567686	10%	-1.616564
RGOLD	1%	-3.963525	1%	-3.434045	1%	-2.566342
	5%	-3.412491	5%	-2.863059	5%	-1.941012
	10%	-3.128198	10%	-2.567626	10%	-1.616572

Table 9. ADF Test for stationarity. Critical values for the returns of all the examined variables.