Cryptocurrencies: Modelling and comparing time-varying volatility – the MGARCH approach

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Abstract

This study quantifies the manner in which the variance of cryptocurrencies behaves compared to this same effect for fiat currencies and indices. Within this comparison, results provide evidence that the past values of the variance of cryptocurrencies have the most effect on the current variance. Furthermore, this effect is shown to be the most persistent as well. By means of using the multivariate generalized autoregressive heteroscedasticity model, it also stated that on average, cryptocurrencies have an exploding variance forecast. Meaning that the variance does not necessarily revert towards a certain mean level of variance.

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I. Introduction

Since the introduction of Bitcoin, it has always been the largest of all cryptocurrencies in terms of market capitalization. It was created in 2008 by an unknown person named Satoshi Nakamoto. The concept was to create a digital peer-to-peer currency that can be transferred instantly and securely between any two parties (Ametrano, 2016). 10 years after the introduction of Bitcoin, over 1500 additional cryptocurrencies (altcoins) have been created. Furthermore, the market capitalization of the total market has increased tremendously since 2008. Not only Bitcoin but also these altcoins contributed to the increasing wealth of the cryptocurrency market. In 2013, the market was worth about $1 billion. At New Year's Eve 2017-2018, the market was worth just over $600 billion (Coinmarketcap, 2018). Next to that, in 2013, Bitcoin dominated the market with approximately 95% in terms of market capitalization. Five years later, after the introduction of over 1500 altcoins, Bitcoin still has a market dominance of about 40%.

The idea for the creation of altcoins is similar to the idea of creating Bitcoin. Namely, creating an alternative and independent money/payment system, operating on the blockchain (Wisniewska, 2016). Since the market capitalization has increased with factor 600 in the past five years, developers hope to create a cryptocurrency that repeats the success of Bitcoin, resulting in huge profits. Also, the creation of subsequent cryptocurrencies is being encouraged because the source code of Bitcoin is open. Therefore, it is relatively easy to create new cryptocurrencies (Wisniewska, 2016).

Furthermore, trading mechanisms have to be in place to trade all these cryptocurrencies. Logically, the trading takes place on online platforms. Several exchanges have been created for this trading since Bitcoin was introduced. Hence, there is also competition between the exchanges in which the currencies are traded on. Network effects are especially important for the operators of the exchanges. This means that a service gets additional value as more people use it. Due to this effect, a cryptocurrency is more useful as people adopt it. Next to that, an exchange is more liquid when there are more buyers and sellers (Gandal and Halaburda, 2014). Thus, a larger exchange is more attractive to new buyers and sellers.

These exchanges are linked to the blockchain system. Just like the internet, blockchain is a communications protocol that governs the rules and regulations for value exchange. Thus, one is the internet of information, while the other is the internet of value (Twesige, 2015). It is the groundwork for transferring cryptocurrencies between two parties. Multiple features make the blockchain an efficient system for processing the transactions. Communication within the system is fast. The system is easily accessible. It is the cheapest system for value exchange at the moment. And finally, it is a transparent system since the ledger of the blockchain is controlled by every computer worldwide (Twesige, 2015). Thus, the blockchain is a digital system on which the transactions of cryptocurrencies take place. Note that the trading of cryptocurrencies of only one feature that can be built upon the blockchain. Whereas the cryptocurrencies themselves are not a general system, but an asset (or a payment method) which are being traded in this relatively new market.

Government agencies have not yet generally accepted this new market worldwide. Overall, governments see two political issues in this case. The first one is taking care of consumer protection issues. For example, electronic theft and the risk of a collapsing value. Secondly, governments are worried about anonymity features of the cryptocurrencies. Meaning that transactions can be made without anyone being able to trace the identity of the person who made the transaction. This anonymity feature could permit the expansion of illegal activities, for example, tax evasion (Blundell-Wignall, 2014). Currently, the rules and regulations for cryptocurrencies differ per country. Nevertheless, the number of stores accepting Bitcoin as a payment method (worldwide) has increased from three at the beginning of 2013 to approximately 11.000 in January 2018 (Coinmap, 2018). This indicates the increasing popularity of the usage of Bitcoin as a payment method and the current acceptance of governments for letting this number increase over the past years.

The purpose of this research arises from the interest in two issues. At first, interest is in the variance of the cryptocurrencies itself. Since a currency needs a relatively stable store of value to act as a proper currency, it is interesting to examine the variance of cryptocurrencies (Yermack, 2015). Secondly, interest is in a comparison to the variance of regular currencies (=fiat currencies) and in a comparison to the variance of indices.

For centuries, people have used several currencies as a medium of exchange. However, since the use of digital currencies is relatively new, it is interesting to examine the differences between the two. More specifically, interest is in the different behaviors of the variances (and thus the stability) of both fiat- and cryptocurrencies. Meaning that this research examines the significance and magnitude in which past values of the variance still affect the variance today. Expectancy is that the variance of cryptocurrencies is much more influenced by its lagged values since these are relatively new and unstable currencies. Hence, a shock in the variance causes more uncertainty about the actual value than in the case of fiat currencies or indices.

Interest in the comparison to the indices arises from the fact that cryptocurrencies are often referred to as assets instead of currencies (Glaser et al., 2014). Once again, it is examined how the behavior of the variance differs in both regressions. Expectancy is similar to the comparison of cryptocurrencies to fiat currencies. Meaning that it is supposed that the variance of cryptocurrencies is much more influenced by its lagged values.

A few papers already made effort in trying to find answers to several other questions relating to the cryptocurrency market. For example, the correlation to equity markets, interests by communities, and the correlation between several cryptocurrencies. However, this paper differs from other papers because it explicitly examines the manner in which the variance of cryptocurrencies behaves on its lagged values. Multiple comparisons are executed to quantify this persistence in the variance as accurately as possible. Additionally, the research differs from others by comparing this to the behavior of the variance of fiat currencies.

To measure and compare this, the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model is used. Hence, it provides quantifiable evidence about the intensity and persistence of the variance of all three categories. It does so by examining the conditional variance model instead of the mean model. The MGARCH model is further explained in the literature review of chapter two and empirically applied and analyzed in chapter four.

To conclude, this research aims to answer the following research question: How do past values of the variance of cryptocurrencies impact the present value of this variance in terms of strength and persistence, compared to this identical effect for fiat currencies and indices?

II. Literature review

This chapter provides information about current literature that is relevant for this research. Subjects that are covered are clustering volatility, the MGARCH model, the dominance of Bitcoin, and the differences between cryptocurrencies, fiat currencies, and indices. Note that in the continuation of this paper, the term ‘volatility’ is often used, since (in finance) this term refers to the standard deviation (= the square root of the variance). Hence, the variance and volatility both measure the variability from an average value. Next to that, both the terms ‘errors’ and ‘residuals’ are used. Whereas the residuals (which are observable from the regression results) are estimates of the unobserved errors.

II.I Clustering volatility

Volatility clustering is one of the most intriguing factors in the modelling of financial time series. Whereas prices themselves appear to be unpredictable, the heights of the percentage changes (absolute returns) appear to be predictable (Gaurnerdorfer, 2007). This means that large changes in prices/returns tend to cluster together. Thus, small changes tend to be followed by small changes, and large changes tend to be followed by large changes (Cont, 2005). Whether this dependence is 'long-term' or 'short-term' is quite relative and can be difficult to quantify. The figure below presents the absolute demeaned returns of the S&P500 to provide some visual intuition behind this phenomenon.

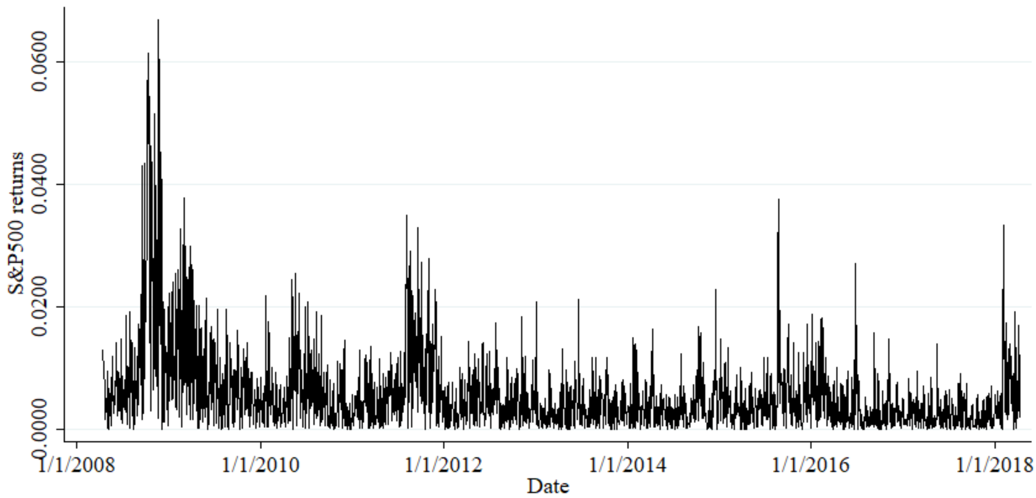

Figure 1: Absolute demeaned returns of the S&P500 over the past 10 years. The graph presents visual evidence that periods of high changes tend to be followed by periods of high changes (and vice versa). For example, the graph shows the relatively high changes during the subprime mortgage crisis (around 2008) and during the Euro-crisis (around 2011).

By means of using the ARCH model, it is pursued to quantify and model this phenomenon of clustering volatility (Cont, 2005). However, a lot of debate emerges around this issue. Analysts argue if there even exists any long-term dependence in volatility. It could be possible that there is no exact measure to quantify this statistical issue. Furthermore, this raises the questions of defining 'presence of clustering volatility' and the concept of 'long-term'. What is long-term in this context? How to measure the significance of the presence of clustering volatility? Thus, the clustering volatility topic has been quite debatable in the past decades.

So, the ARCH model provides statistical constructions that mimic the clustering of volatility in financial time series. However, it does not provide any economic intuition behind the phenomenon. In the current state of literature, several mechanisms have been proposed for being the origin of volatility clustering (Cont, 2005).

One of the theories about the origin of this phenomenon states that short-term traders aim to exploit short-term fluctuations in the market. This should strengthen the effect of volatility clustering (Guillaume et al., 1997). Hence, this relates the theories about behavioral finance. Overall, many current theories about this concept strongly relate it to behavioral finance. For example, Lux and Marchesi (2000) studied if volatility clustering arises from behavioral switching of market participants between fundamentalists and 'noise traders'. Fundamentalists believe that the price of an asset follows a fundamental value over time, whereas so-called noise traders aim to exploit fluctuations in the market. The theory states that price changes in the market should be stable most of the time due to a balance between demand and supply. However, in phases of destabilization, an outbreak of volatility occurs due to trading techniques of the noise traders. This behavioral switching is belied to be the cause of volatility clustering in financial time series (Lux and Marchesi, 2000).

Of all these academics to investigate the phenomenon, Mandelbrott (1971) was the first to create the idea of the possibility of long-term dependence in (stock) returns. Thus, empirical studies of Mandelbrott did show the presence of clustering volatility back in 1971 and other academics have built upon the intuition of the concept ever since. However, academics have also criticized these empirical studies for being statistically incorrect. For example, after controlling for short-term dependence, results would already be completely different (Cont, 2005). Hence, conclusions became less clear about the actual occurrence and persistence of clustering volatility.

Nevertheless, it is important not to ignore this phenomenon since the volatility is a key feature for measuring risk in financial time series. Moreover, volatility clustering violates the assumption of the variance being constant over time. Meaning that many financial models would obtain inaccurate results when assuming homoscedasticity in cases of volatility clustering (Tewari, 2013).

In case of an ordinary least-squares (OLS) regression, estimates of the regression coefficients would be inefficient in the event of volatility clustering. Meaning that they are no longer minimum variance estimates (Tewari, 2013). Hence, it is important to gain insight into the behavior of the volatility and the manner in which it can cluster (Gaurnerdorfer, 2007). Therefore the MGARCH model is used. Since this research is executed by means of the MGARCH model, the intuition and existing literature about the model are also presented.

II.II MGARCH model

In financial time series, it is commonly observed that periods of relatively high volatility and relatively low volatility are grouped together. ARCH models seek to estimate the volatility as a function of the prior volatility. The popularity of this model (as well as the popularity of the GARCH model) comes from being able to deal with heteroscedasticity and the ability to model nonlinear dynamics (Tewari, 2013). Thus, instead of considering heteroscedasticity as a problem to be corrected, the ARCH/GARCH model treats heteroscedasticity as a variance to be modeled. By doing so, the deficiencies of OLS are corrected and a prediction can be computed for the variance of the error term (Engle, 2001).

ARCH

The traditional ARCH model was introduced by Robert F. Engle in 1982. Engle constructed the model because traditional econometric models assume a constant forecasted variance. According to Engle, this was an implausible assumption. In the ARCH model, both the conditional mean and the conditional variance are modeled. In the model for the conditional variance, the variance of the dependent variable is a function of the squared lagged value of the residual:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 \epsilon_{t-2}^2 + \cdots + \gamma_m \epsilon_{t-m}^2 = \gamma_0 + \sum_{i=1}^{m} \gamma_i \epsilon_{t-i}^2$$

Furthermore, the formula for the conditional mean model is stated in the equation below. However, for this research, interest is only in the model of the conditional variance.

$$y_t = x_t \beta + \epsilon_t$$

GARCH

In the GARCH model, the equation for the conditional variance is extended. Now the variance of the dependent variable is a function of both the squared lagged value of the residual and of its own lagged value:

$$\sigma_t^2 = \gamma_0 + \gamma_1\epsilon_{t-1}^2 + \gamma_2\epsilon_{t-2}^2 + \cdots + \gamma_m\epsilon_{t-m}^2 + \delta_1\sigma_{t-1}^2 + \delta_2\sigma_{t-2}^2 \dots + \delta_k\sigma_{t-k}^2$$

$$= \gamma_0 + \sum_{i=1}^{m}\gamma_i\epsilon_{t-i}^2 + \sum_{i=1}^{k}\delta_i\sigma_{t-i}^2$$

Where, σ_t^2 is the variance, ϵ_t^2 is the squared residual, γ_0 is the constant term, γ_m are the ARCH parameters and δ_k are the GARCH parameters.

The GARCH model can be considered an ARMA (autoregressive moving average) process. This is a stationary process (=mean and variance do not change over time) that can be expressed into two algebraic terms. The first one is the autoregression and the second one is the moving average. The autoregressive (AR) part concerns about regressing the variable on its own lagged values. The moving average (MA) part concerns about modelling the error term at various times in the past. The ARMA formula is as follows:

$$x^t = c + \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_m x_{t-m} + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} \dots + \theta_k\epsilon_{t-k}$$

$$= c + \sum_{i=1}^{m}\emptyset_i x_{t-i} + \sum_{i=1}^{k}\theta_i\epsilon_{t-i}$$

Note that GARCH is a model that captures volatility dynamics of ARMA type models. Hence, both models are built upon the same idea of explaining a variable upon its own lagged values and the lagged values of the error terms.

The GARCH model has proven to be useful for empirically capturing the momentum in conditional variance. "Under GARCH, shocks to variance persist according to an autoregressive moving average structure of the squared residuals of the process. Much of the recent evidence from financial-market data seems to suggest that persistence in variance, as measured by ARCH models, is quite substantial (Lamoureux and Lasptapes, 1990)." Thus, the model tries to measure the future volatility as a function of the volatility in the past. It does so by using numerical maximum likelihood estimation. Meaning that the model chooses to quantify the parameters γ_m and δ_k (=ARCH and GARCH parameter) based on the maximization of the likelihood of the observations occurring.

Additionally, this model is able to capture the correlation of the volatility between two markets. The model accomplishes this either directly through its conditional variance or indirectly through its conditional covariance's (Lean and Teng, 2013). The model is also able to examine the volatility spillover from one market to another market. Next to that, the model takes care of clustered errors and nonlinearities in the regression (Matei, 2009).

The original GARCH model is based on the normal (Gaussian) distribution. However, the normal distribution cannot accommodate to the fat-tail disturbance that occurs in financial time series. The Student's t-distribution and General Error Distribution (GED) are usually used to solve this problem. However, a study by Calzolari in 2014 points out that those alternative distributions lack stability under aggregation (Feng, 2017). Therefore, this research applies the normal distribution when running the MGARCH model.

MGARCH

The success of the autoregressive conditional heteroscedasticity (ARCH) model and the generalized ARCH (GARCH) model in capturing the time-varying variances of economic data in the univariate case has motivated many researchers to extend these models to the multivariate dimension (Minović & Simeunović, 2008). Consequently, in 1988, the first GARCH model for the conditional covariance matrices (=MGARCH) was introduced. This model (which is used in this research) is an extension of the ARCH/GARCH model.

For this research, the MGARCH model is used because this model is used for the joint modelling of several time series. Hence, the GARCH model is for modelling a single time series, and the multivariate model is for the modelling of two or more time series. Meaning that the volatility of one time series is influenced by both its own past values and the past values of the other time series in the regression.

Furthermore, the coefficients of the MGARCH model have to be interpreted as described below. For the creation of examples of these interpretations, it is assumed that the values of all the coefficients are equal to 0.5.

- $\boldsymbol{\gamma_0}$ $(\boldsymbol{gamma})$ (=constant term): represents the long-run average variance. Hence, the mean reversion goes towards this level of variance. However, this is only the case if there is presence of mean reversion. If $\gamma_1 + \delta_1 < 1$ then there is mean reversion. If $\gamma_1 + \delta_1 > 1$ then there is an exploding variance forecast (Rizvi and Arshad, 2013).

- $\boldsymbol{\gamma_m}$ $(\boldsymbol{gamma})$ (=ARCH parameter): under the assumption that the GARCH parameter equals 0, one unit increase (decrease) of the lagged residual term leads to a 0.5 increase (decrease) of the variance of the dependent variable in the regression. Hence, the ARCH parameter measures the extent to which a volatility shock today feeds through into next period's volatility (Campbell, Lo, & MacKinlay, 1997, p.483).

- $\boldsymbol{\delta_k}$ $(\boldsymbol{delta})$ (=GARCH parameter): one unit increase (decrease) of the lagged variance term (of the dependent variable) leads to a 0.5 increase (decrease) of the variance of the dependent variable in the regression. Hence, if this parameter increases, it means that larger changes in the volatility affect future volatilities for a longer period of time (since the decay in slower). Since the ARCH-model is extended in this case, the effect on the variance of the dependent variable has to be compounded with the ARCH-term.

- $\boldsymbol{\rho_{yz}}$ $(\boldsymbol{rho})$ (=correlation parameter): a correlation term of 0.5 means that the correlation between the error terms of y and z is equal to 0.5. This indicates one unit increase (decrease) in the variance of y leads to a '0.5*$\left(\frac{\gamma_{0y}}{1-(\gamma_{1y}+\delta_{1y})}\right) / \left(\frac{\gamma_{0z}}{1-(\gamma_{1z}+\delta_{1z})}\right)$' increase (decrease) in the variance of z. Hence, the impact of the correlation parameter also depends on the constant-term, ARCH-term, and GARCH-term of both currencies.

- $\boldsymbol{\lambda_n}$ $(\boldsymbol{lambda})$**:** lambda shows if periods of high correlation are followed by periods of high correlation (and vice versa). A value close to 1 indicates a slow decay of the effect, meaning that the persistence is longer. If it is observed that the summation of λ_1 and λ_2 is less than one, the returns in the data are not following IGARCH (=integrated generalized autoregressive conditional heteroscedasticity). This indicates that shocks in the variance are not permanent over time. Hence, this implies some form of decay in the persistence of the effect of the lagged residuals and the lagged variance on the current variance (Rizvi and Arshad, 2013).

  Furthermore, λ_1 and λ_2 represent the ARCH-term and GARCH-term respectively. Hence, a larger λ_1 implies that the lagged residuals (γ_m) have more importance than the lagged values of the variance(δ_k). On the other hand, a larger λ_2 implies that the lagged values of the variance have more importance than the lagged residuals. The fact that these values are statistically different than zero can be evidence that conditional covariances are time-varying. Meaning that the DCC (dynamic conditional correlation) variant of the MGARCH regression is the most appropriate to use. This variant of the model does not assume that the conditional correlation matrix is constant. In other words, DCC assumes time-variation in the conditional variances, and CCC (constant conditional correlation) assumes it to be constant (Cardoso and Bittencourt, 2014). Thus, the DCC-GARCH model is a generalization of the CCC-GARCH model, which allows the correlation matrix to depend of the time (Orskaug, 2009).

Briefly summarized, the coefficients of the model used in this research provide information about the variance in the market and how it reacts over time upon its own lagged values and the lagged values of the error terms.

II.III Bitcoins influence on altcoins

Since the MGARCH model also captures the volatility spillover between two variables, interest is in the influence of Bitcoin on other cryptocurrencies. The presence of this influence of Bitcoin is a plausible assumption since Bitcoin still occupies about 40% of the total market capitalization (April 2018). However, this dominance has declined in the past years. In January 2014, Bitcoin occupied about 87.5% of the total market capitalization (Coinmarketcap, 2018). Nevertheless, the fact that Bitcoin is influential over altcoins is quite intuitive. Bitcoin gained its dominance in the market by being the first cryptocurrency to exist. Nowadays, other altcoins have to be bought with Bitcoin. Hence, if the value of Bitcoin rises, investors have more value available to buy altcoins. This increase in demand could logically lead to a likewise increase of the altcoin prices. Hence, it is expected that the correlation between the cryptocurrencies higher compared to the fiat currencies and the indices.

Multiple studies have investigated the effect of price changes in Bitcoin on several altcoins. In one of these studies, the influence of Bitcoin on altcoins was empirically confirmed. In 2015, Cizek showed that the returns of Bitcoin do have a positive impact on both Litecoin, Ripple, Peercoin, and Dogecoin in the short term. Cizek explains this effect by stating that all currencies are (to some extent) very similar. Therefore, investors treat both Bitcoin and altcoins as substitutes. This could indicate that the variance of all cryptocurrencies persists through time in somewhat the same way as well.

In the long run, the influence of Bitcoin has somewhat the same explanation. Long-term effects can be due to gaining (losing) faith in the market resulting in a collective bullish (bearish) behavior of the investors (Cizek, 2015). Hence, the overall reputation in the market is crucial for the price development of all cryptocurrencies. This automatically creates a connection between the returns of all cryptocurrencies, since the reputation of the market affects all of the cryptocurrencies on the market. Important events (such as announced regulations) cause enormous media attention in the crypto community (Cizek, 2005). These events can cause the overall reputation of the market to rise (fall), resulting in bullish (bearish) behavior on all cryptocurrencies.

This long-term effect was empirically examined by Catania and Grassi in 2017. The authors found long-term memory in the volatility of cryptocurrencies in a time series dataset. Hence, the volatility of the past can indeed have influence on the volatility of Bitcoin (or an altcoin) today. This observation by Catania and Grassi strengthens the expectancy of this research of finding a positive effect of the past errors and variances to influence today's variance.

II.IV Cryptocurrency or crypto-asset

According to the European Central Bank (2012) and Kaplanov (2012), a currency is something that can be used as a store of value, an exchange mechanism, and a unit of account to compare values of different goods. Furthermore, according to Merriam Webster, the definition of a currency is something (such as coins, treasury notes, and banknotes) that is in circulation as a medium of exchange. Next to that, the definition of an asset is an item of value owned (Merriam Webster, 2018).

While analyzing both definitions, any cryptocurrency seems to be both a currency and an asset. The name 'cryptocurrency' implies that it is indeed a currency. However, since the definition of an asset also fits the characteristics, it is hard to tell which one fits best. This paragraph describes the current theoretical debates considering this topic. This is relevant for this research since interest is also in a comparison of the variance of cryptocurrencies to other types of currencies/assets.

According to Laidler (1969), the problem in this case is whether assets over which the (monetary) authorities have control may be regarded as valid 'currencies'. Note that the problem statement refers to 'assets' specifically and hence, does not refer to valid fiat currencies. Contrarily, cryptocurrencies are not recognized as a valid currency everywhere and can therefore be considered as an asset in this statement.

So, since cryptocurrency transactions are peer-to-peer and therefore do not move through any governmental institutes, it would have been defined as a currency according to Laidler. However, cryptocurrencies are also controlled by a certain (non-governmental) institute. These are authorities of which it is plausible that influence on the valuation and continuation of a specific cryptocurrency is within the control of this institute. Logically, these influential authorities over cryptocurrencies are the companies who developed it and placed it in the market. Hence, it is possible for developers to buy/sell/create considerable amounts of cryptocurrencies and influence the price by doing so. Therefore, considering the definition of Laidler, cryptocurrencies should be considered an asset. A valid currency needs to be stable and non-influential for external sources to diminish the risk of losing too much value (Laidler, 1969).

Nevertheless, since the introduction of Bitcoin, the number of stores accepting Bitcoin as a valid currency has increased tremendously. At the beginning of 2013, three stores accepted Bitcoin worldwide. In January 2018, this number has increased to approximately 11.000 (Coinmap, 2018). This indicates that the acceptance of Bitcoin is increasing. However, when examining the definition of 'a currency' in this paragraph, it states (among others) that it has to be able to be used as a store of value. Since Bitcoin has been a relative highly fluctuating asset/currency over the past years, it is quite remarkable that stores still accept Bitcoin as a currency. In order to store value over time, users need to quantify the expectations about the future value of the cryptocurrency (Glaser et al., 2014). Especially for stores, since the profits (partly) depend on the value of Bitcoin at a certain point in time.

In order to determine the value of a currency in the future, an indication of the interest rate is quite substantial. "Bitcoin, however, does not provide the feature of an interest rate in contrast to fiat currencies, where interest rates are provided by central banks and interest rate term structures are derived from bonds with differing maturities" (Glaser et al., 2014, p 5). Thus, a future valuation of cryptocurrencies cannot be based on a given interest rate. Therefore, the investors of cryptocurrencies are completely left alone in determining the value. The value is based on what the investor's belief the expected value to be in the future. Since this is dependent on a considerable amount of factors, it is hard to predict the future value of cryptocurrencies. Hence, is it hard to use cryptocurrencies as a store of value, and thus, to consider it a valid currency.

To conclude, it is debatable whether or not cryptocurrencies have to be considered an asset or a valid currency since it matches in characteristics of both. For now, it is irrelevant for cryptocurrencies whether it derives its value from a speculative perspective (asset) or a transactional perspective (currency). This research considers it to be part of both. The next chapter expresses how this is further adopted in this research.

III. Data

The first paragraph of this chapter provides a description of the data. Meaning that it presents descriptive statistics of the data, computations of how this data was acquired, and graphs to visualize the data. Afterward, the methodology is specified.

III.I Data description

Data description is specified in three sub-paragraphs. The first one to cover the data of the cryptocurrencies. The second one to cover data of fiat currencies. The third one to cover data of indices, since these are considered as assets. Data for both fiat currencies and indices are used since it is debatable whether cryptocurrencies are an asset or a valid currency. Therefore, it is interesting to make a comparison between these two classes and the cryptocurrencies.

III.I.I Cryptocurrency data

At first, data of the top 50 largest cryptocurrencies have been gathered and organized in Excel. The selection of 'largest' coins is based on the market capitalizations for the individual coins as of 15-4-2018. Therefore, all data collected for this research runs up until this date. However, the first dates to contain data differs for every cryptocurrency, since the ICO-dates differ in each case. For each of these cryptocurrencies, the daily price, daily volume, and the market capitalization have been gathered. The data is collected from Coinmarketcap. This website uses a weighted average of multiple crypto-exchanges to compute the daily price. Furthermore, the value of each cryptocurrency is expressed in terms of the American dollar (USD).

To carry out this research, seven 'portfolios' are constructed. Six individual ones and one altcoins package that contains data of fifteen altcoins. The individual coins are selected based on highest trading volume (with the criteria of having at least 250 daily data available). Since these are the most liquid altcoins (and thus, often traded in this market), it is more effective to find any kind of similarity in the behaviour of Bitcoin and the altcoins.

The returns of the altcoin package are computed by taking the average of the individual returns of the fifteen altcoins. Consequently, for the computation of the conditional standard deviation of this variable, these average daily returns are used. Note that the term 'volatility' also refers to the conditional standard deviation in this research.

Furthermore, the altcoins package contains fifteen altcoins that are selected on having the most daily data available (excluding the coins that are already selected in the individual section). The altcoins that are selected for this altcoin package are:

- Dogecoin (DOGE)
- Bytecoin (BCN)
- Verge (XVG)
- Lisk (LSK)
- Waves (WAVES)
- Dash (DASH)
- Bitshares (BTS)
- NEM (XEM)
- Steem (STEEM)
- Ethereum Classic (ETC)
- Monero (XMR)
- Stellar (XLM)
- Siacoin (SC)
- DigixDAO (DGD)
- Stratis (STRAT)

For these comparisons, the altcoins 'Tether' and 'Bitcoin Cash' were excluded from the previously described selection process. Tether is excluded because it is linked to the USD. Thus, one Tether is always worth $1, making this comparison not very interesting for this research (since it does not have any change in returns when it is expressed in terms of

USD). Next to that, Bitcoin Cash is excluded from the selection because it is originated from a fork of the Bitcoin. Therefore, it automatically has a connection to Bitcoin, making it less interesting to examine the relationship between the two for this particular research. The table below shows the seven portfolios used in this research, including the dominance of the specific coin(s) in the market (based on market capitalization).

No.	Name	Market Cap	Market Cap / Total Market Cap
1	Bitcoin	$ 137.457.941.053	42,92%
2	Ethereum	$ 50.534.138.957	15,78%
3	Ripple	$ 25.232.558.148	7,88%
5	Litecoin	$ 7.188.358.061	2,24%
6	EOS	$ 6.544.301.145	2,04%
10	NEO	$ 4.263.830.565	1,33%
-	Altcoin package	$ 22.133.131.796	6,91%

Table 1: Cryptocurrencies used in this research and the market capitalizations as of 15-4-2018. The 'No.-column' indicates the rank of that specific cryptocurrency based on its market capitalization.

Hence, the data of the daily volumes are used to create the selection for these seven portfolios. Next to that, the data of the market capitalizations shows the dominance of Bitcoin over the selected altcoins.

For each cryptocurrency, two variables are obtained. At first, the daily value/price of that specific currency expressed in terms of USD. The descriptive statistics of these variables are shown in the table below.

Variable	Obs	Mean	Std. Dev.	Min	Max
BTCPrice	1,814	1698.781	3169.146	69.39	19308.3
ETHPrice	983	172.5767	279.8528	.439459	1382.125
LTCPrice	1,814	24.67773	52.59889	1.215	354.69
XRPPrice	1,716	.1176122	.33385	.0029455	3.235
EOSPrice	289	4.696474	4.109305	.5038625	15.075
NEOPrice	584	27.90943	40.53567	.0808405	178.755

Table 2: Descriptive statistics of the price variables of all six individual cryptocurrencies. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable. The altcoin portfolio is not in this table since information about the average prices and such would not make any sense.

Secondly, the daily return is computed for each fiat currency. This computation is done by means of the following formula:

$$\text{Returns: } r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$
$$where, r = return \quad p = price\ at\ that\ day$$

The log return-formula is used here instead of the other formula that is commonly used ($r = (p_t - p_{t-1})/p_{t-1}$) for return computations. The log formula is used because of the time additivity property. Meaning that a two period log return is equal to the sum of these two individual log returns. Hence, if the returns of the commonly used formula are inserted in the formula below, the product of normally-distributed variables is not normal.

$$(1 + r_1)(1 + r_2) \dots (1 + r_n) = \prod_{i}^{n}(1 + r_i)$$

Therefore, log returns are used in this research. Furthermore, it is approximately good for short periods, for example, in daily data. The table with descriptive statistics of the returns of all seven portfolios is shown below.

Variable	Obs	Mean	Std. Dev.	Min	Max
BTCreturn	1,813	.0022637	.0320458	-.2045889	.2517133
ETHReturn	982	.0053146	.0622812	-.9228719	.2909661
LTCReturn	1,813	.0018743	.0500153	-.307817	.5883975
XRPReturn	1,715	.0027516	.0594301	-.3824862	.644149
EOSReturn	288	.0073681	.090501	-.1984077	.6082984
NEOReturn	583	.0089261	.0848007	-.4050916	.6409812
AltsReturn	611	.0064171	.0445355	-.1969883	.1670281

Table 3: Descriptive statistics of the return-variables of all seven portfolios. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable. As presented in the table, the mean returns are all positive. Furthermore, it is noticed that the minimum and maximum value of the altcoin portfolio are the smallest of all seven portfolios. This is due to the combination of several altcoins, which cancels out very large outliers.

After the data was organized in Excel, it was imported into Stata to use it for the continuation of this research.

III.I.II Fiat currency data

The data of the fiat currencies used in this research are gathered from the website of Finanzen. This website is the largest portal in Germany to gather financial data (Finanzen, 2018). For this research, data has been gathered and organized in Excel for six fiat currencies. A total of six currencies are chosen since the data for cryptocurrencies also consists of six individual cryptocurrencies. The currencies are selected based on having the largest exchange market turnover on a worldwide basis as of April 2016. Data for carrying out this selection is obtained from a paper of the Bank for International Settlements – Triennial Central Bank (Triennial Central Bank, 2016). Based on this criteria, the following six fiat currencies are selected:

- Euro (EUR)
- British pound (GBP)
- Australian dollar (AUD)
- Japanese yen (JPY)
- Canadian dollar (CAD)
- Swiss franc (CHF)

The American dollar is not in this selection because the value of these currencies is expressed in terms of the dollar. By doing so, the value of the fiat currencies is influenced by the fluctuation of the dollar in the same way as it does to the cryptocurrencies (since these are also expressed in terms of the American dollar).

Data is gathered from 28-4-2013 up until 15-4-2018. This time period is specifically chosen since it is the same time period for which data Bitcoin has been gathered. Similar to the data of the cryptocurrencies, the daily values are obtained. Note that the difference compared to the cryptocurrency data is that data for fiat currencies can only be obtained for weekdays.

For each fiat currency, two variables are obtained. At first, the daily value/price of that specific currency expressed in terms of USD. The values obtained originate from the average of the opening price and closing price on that day. The descriptive statistics of these variables are shown in the table below.

Variable	Obs	Mean	Std. Dev.	Min	Max
EURUSD	1,295	1.195084	.1081092	1.0396	1.39275
GBPUSD	1,295	1.467914	.1436379	1.2056	1.7161
AUDUSD	1,295	.8105034	.0811879	.6866	1.03595
JPYUSD	1,295	.0091323	.0006422	.0079982	.0106039
CADUSD	1,295	.8248617	.0800924	.6863656	.9964629
CHFUSD	1,295	1.04764	.042355	.9716758	1.165773

Table 4: Descriptive statistics of the price variables of all six fiat currencies. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable.

Secondly, the daily return is computed for each fiat currency. This computation is done in the same manner as with the cryptocurrency data:

$$\text{Returns: } r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$
$$where, r = return \quad p = price\ at\ that\ day$$

Variable	Obs	Mean	Std. Dev.	Min	Max
EURreturn	1,294	-.0000449	.0037134	-.0184281	.0154129
GBPreturn	1,294	-.0000655	.0042052	-.0639596	.0170446
AUDreturn	1,294	-.0002195	.0043578	-.0192269	.0153176
JPYreturn	1,294	-.0000711	.0042561	-.022335	.0235116
CADreturn	1,294	-.0001677	.0034627	-.0162491	.0145869
CHFreturn	1,294	.0000187	.0050818	-.0899891	.0175756

Table 5: Descriptive statistics of the return-variables of all six fiat currencies. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable. Note that the daily volatility for all fiat currencies is roughly 10 to 15 times lower than those of the cryptocurrencies.

Similar to the cryptocurrency data, the data for fiat currencies was imported into Stata after organizing it in Excel.

III.I.III Indices data

The data of the indices is gathered from the website of Yahoo Finance. This website is part of Yahoo!'s network and it provides financial data (Yahoo! Finance, 2018). For this research, data from six indices are gathered. A total of six indices are chosen since the data of the cryptocurrencies and the fiat currencies also consists of six individual currencies. The selection of the six indices started by examining the countries with the largest nominal GDP worldwide (Statistics Times, 2018). Afterward, the largest index of each of these counties was selected. Based on this criteria, the following six counties and indices are selected:

- USA (Dow Jones Industrial Average)
- Japan (Nikkei 225 Stock Average)
- France (CAC40)
- China (SSE Composite)
- Germany (DAX30)
- England (FTSE100)

Data is gathered from 28-4-2013 up until 15-4-2018. This time period is specifically chosen since it is the same time period for which data Bitcoin has been gathered. Similar to the data of the cryptocurrencies, the daily values are obtained. Note that the difference compared to the cryptocurrency data is that data for indices can only be obtained for weekdays.

For each index, two variables are obtained. At first, the daily points of that specific index. The values obtained originate from the average of the number of points at the opening of the market and the number of points at the closing of the market on that day. The descriptive statistics of these variables are shown in the table below.

Variable	Obs	Mean	Std. Dev.	Min	Max
USA	1,295	18455.59	2721.932	14715	26541.73
CHN	1,292	2936.503	640.509	1952.569	5154.846
JPN	1,294	17710.52	2567.109	12677.71	24024.28
GER	1,295	10587.6	1424.597	7734.665	13568.37
FRA	1,295	4639.663	447.2233	3624.075	5549.41
ENG	1,295	6781.118	439.527	5604.635	7773.89

Table 6: Descriptive statistics of the daily points of every index. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable. Note that China and Japan miss three and one data-points respectively (compared to the other countries). This is due to missing data in Yahoo! Finance of the Asian market at the beginning of the time series.

Secondly, the daily return is computed for every index. This computation is done in the same manner as with the cryptocurrency data and the fiat currency data:

$$\text{Returns: } r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$
$$where, r = return \quad p = price\ at\ that\ day$$

Variable	Obs	Mean	Std. Dev.	Min	Max
USAreturn	1,294	.0003904	.0054881	-.037512	.0301557
CHNreturn	1,291	.0002941	.011885	-.0979538	.0602444
JPNreturn	1,293	.00035	.0105858	-.0480673	.0414612
GERreturn	1,294	.0003562	.0090639	-.0809503	.0332442
FRAreturn	1,294	.0002497	.0087987	-.0760106	.0401006
ENGreturn	1,294	.0000925	.0060772	-.0380712	.030694

Table 7: Descriptive statistics of the returns of the six indices. The table presents the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of each variable. Note that the daily volatility is on average smaller than those of the cryptocurrencies, but larger than those of the fiat currencies. Furthermore, China and Japan miss three and one data-points respectively (compared to the other countries). This is due to missing data in Yahoo! Finance of the Asian market at the beginning of the time series.

Once again, the data of the indices was imported into State after organizing it in Excel.

III.II Methodology

This research is executed by using the MGARCH model. The choice for this model arises from the strong plausibility of clustering volatility. The graphs below show the absolute demeaned returns of all seven cryptocurrency portfolios over time to examine this in a visual manner.

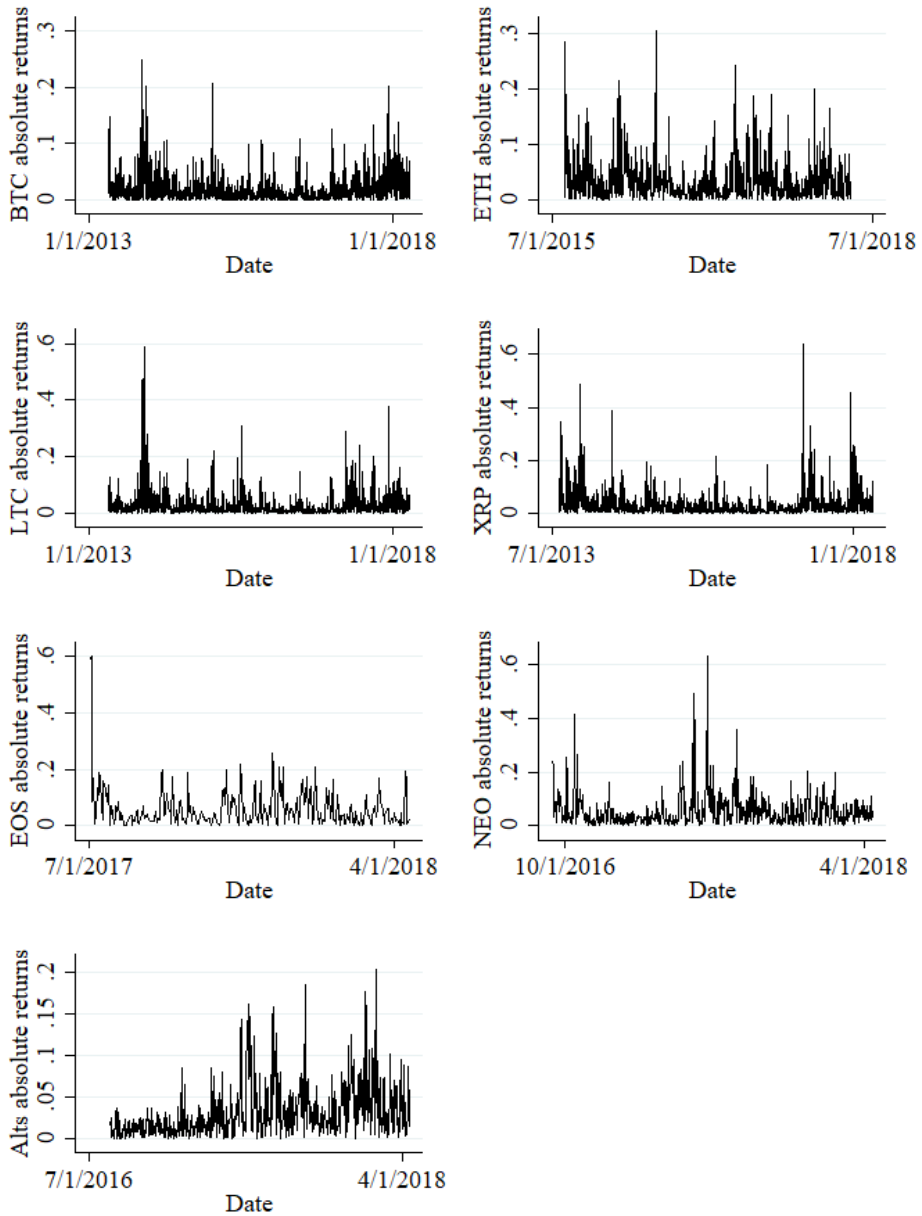

Figure 2: The absolute demeaned returns over time of all seven cryptocurrency portfolios are presented in a line graph. Graphs above provide such information that volatility clustering seems plausible.

The MGARCH model is especially useful in cases of clustering volatility since it corrects for this phenomenon in financial data. The table confirms the idea of volatility (=conditional variance) being persistent: large (small) values are likely to be followed by large (small) values (Fryzlewicz, 2007). Hence, by using the MGARCH model, this statistical problem of clustering volatility can be captured.

A total of three MGARCH regressions are executed in this research. One for the cryptocurrencies, one for the fiat currencies, and one for the indices. These regressions are executed in Stata. In all regressions, a dynamic conditional correlation (DCC) is used on the normal (Gaussian) distribution. All the return-variables are used at the same time as input for a single regression. Hence, the variables of the prices/points were solely used to gather the data of the returns. Furthermore, the lags for both the ARCH- and the GARCH-parameter are set to 1. After running the regressions, all the coefficients of the output of the cryptocurrency regression are interpreted individually. Subsequently, these coefficients are compared to those of the fiat regression and the index regression. Interest is in the behavior of the variance of the cryptocurrencies itself, and in the comparison to the other two regression.

IV. Modelling time-varying volatility

This chapter contains two paragraphs. The first one to analyze the MGARCH output of the cryptocurrency regression. The second one to compare these results to the MGARCH output of the fiat currency regression and the indices regressions. The coefficients and the standard deviations of the regressions are rounded to four decimals. Thus, any value lower than '0.00005' is presented as being equal to 0.

IV.I Result for cryptocurrencies

The table below displays the results of the MGARCH regression of the cryptocurrencies. All the return variables are taken as dependent variables.

MGARCH - cryptocurrencies		γ_0	γ_1	δ_1
BTC	Coef.	0.0006	**0.5509**	**0.3283**
	Std. Err.	0.0001	0.0963	0.0814
	z	4.21	5.72	4.03
	P>z	0.000	0.000	0.000
ETH	Coef.	0.0007	**0.6048**	**0.2972**
	Std. Err.	0.0002	0.0955	0.0877
	z	3.96	6.33	3.39
	P>z	0.000	0.000	0.000
LTC	Coef.	0.0014	**0.6847**	**0.1090**
	Std. Err.	0.0003	0.1115	0.0733
	z	5.31	6.14	1.49
	P>z	0.000	0.000	0.137
XRP	Coef.	0.0005	**0.6889**	**0.4653**
	Std. Err.	0.0001	0.1067	0.0427
	z	5.14	6.46	10.90
	P>z	0.000	0.000	0.000
EOS	Coef.	0.0028	**1.1691**	**0.0149**
	Std. Err.	0.0005	0.1872	0.0323
	z	5.97	6.25	0.46
	P>z	0.000	0.000	0.646
NEO	Coef.	0.0011	**0.4373**	**0.4996**
	Std. Err.	0.0003	0.0874	0.0707
	z	3.91	5.00	7.06
	P>z	0.000	0.000	0.000
Alts	Coef.	0.0009	**0.4254**	**0.4417**
	Std. Err.	0.0002	0.0687	0.0748
	z	4.30	6.19	5.90
	P>z	0.000	0.000	0.000

Table 8: Stata output of MGARCH regression of the cryptocurrency class. The table presents the constant, the ARCH-parameter, and the GARCH-parameter for every cryptocurrency (portfolio). For every parameter and every portfolio, the regression coefficient, the standard error, the z-value, and the 'P>z' value (a measure of significance) are presented.

At first, the p-values are analyzed to conclude if it is optimal to include all dependent variables together. In the event that both the ARCH- and the GARCH-parameter are insignificant for one particular variable, the model would be improved by removing this variable (Stata, 2018). The table shows that all the coefficients are statistically significant at a 1-percent level (except for the $\delta_{1,LTC}$ -, and the $\delta_{1,EOS}$-parameter). Hence, there is no interest in removing any of the variables in the regression.

Secondly, the ARCH-parameters (γ_1) indicate that the one-period lagged values of the residuals do have influence on the variance today. For example, one unit increase of the one-period lagged residual term of Bitcoin leads to a 0.5509 increase of the variance of Bitcoin in the current period. This is under the assumption that the GARCH parameter equals 0. Furthermore, this parameter is shown to be the smallest in the case of the altcoin portfolio. Indicating that the individual cryptocurrencies (which are selected based on having the highest liquidity) have a stronger ARCH-effect than the altcoin portfolio.

Thirdly, the GARCH-parameters (δ_1) indicate that the one-period lagged values of the variance do have influence on the variance today. Exceptions are for the GARCH-parameters of the Litecoin and the EOS variable. For Litecoin, this variable only has a p-value of 0.1370, indicating that the effect less interesting to interpret compared to the significant coefficients. For EOS, the variable has a p-value of 0.6460, indicating that the strength of the effect is negligible. Nevertheless, the other coefficients are interesting to analyze. For example, one unit increase of the one-period lagged variance term of Bitcoin leads to a 0.3283 increase of the variance of Bitcoin in the current period.

At last, for an accurate interpretation, note that adding this GARCH-parameter in the regression results in the fact that the effect on the variance of the dependent variable has to be compounded with the ARCH-term. Hence, the behavior of the variance depends on both the lagged residuals and the lagged variance. Whether these effects are strong is a relative concept to interpret. Therefore, a comparison is made in the next paragraph to investigate the strength of these effects.

To provide more intuition in this comparison, two graphs are illustrated on the next page. These graphs present the volatility of both Bitcoin and Litecoin in the time period 28-4-2013 up until 15-4-2018. These graphs provide additional clarity in the phenomenon mentioned above. Namely, that the volatility shock today feeds through into next period's volatility and that this effect is quite persistent. The first graph presents the volatility of Bitcoin, and the second graph presents the volatility of Litecoin. Note that the values on the y-axis are values of the volatility on a daily basis. Meaning that the daily volatility can be up to approximately 20% to 30% in extreme events.

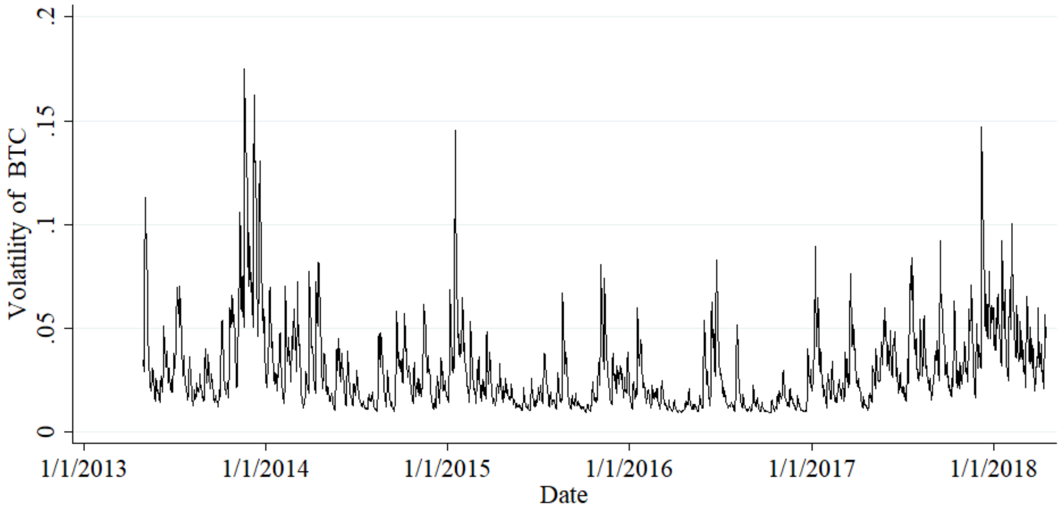

Figure 3: Daily volatility (square root of the conditional variance) of Bitcoin. This filtered volatility of Bitcoin is obtained after running the MGARCH model solely for Bitcoin. Afterward, Stata predicted these values for the conditional daily volatility. The graphs show the effects named above. Namely, that periods of high volatility tend to be followed by periods of high volatility (ARCH effect), and that this effect is quite persistent as well (GARCH effect). Especially in the periods around late 2013 and late 2017 (which are exactly the periods in which Bitcoin made its highest increases).

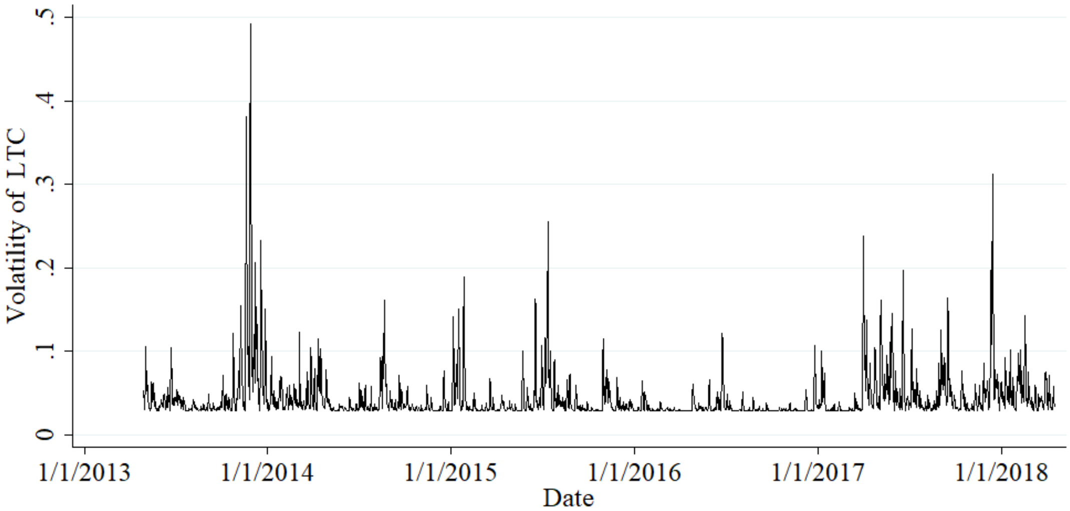

Figure 4: Daily volatility (square root of the conditional variance) of Litecoin. This filtered volatility of Litecoin is obtained after running the MGARCH model solely for Litecoin. Afterward, Stata predicted these values for the conditional daily volatility. The graphs show the effects named above. Namely, that periods of high volatility tend to be followed by periods of high volatility (ARCH effect), and that this effect is quite persistent as well (GARCH effect).

Additionally, the MGARCH regression also provides coefficients that quantify the correlation between the variables (ρ_{yz}), and coefficients of the persistence of both the ARCH and GARCH effects (λ_1)&(λ_2). Results are shown in the table below.

MGARCH - cryptocurrencies				
$\boldsymbol{\rho}$	Coef.	Std. Err.	z	P>z
BTC,ETH	0.7596	0.0373	20.37	0.000
BTC,LTC	0.7691	0.0350	21.95	0.000
BTC,XRP	0.6335	0.0529	11.98	0.000
BTC,EOS	0.6556	0.0504	13.01	0.000
BTC,NEO	0.6282	0.0527	11.92	0.000
BTC,Alts	0.7970	0.0343	23.26	0.000
ETH,LTC	0.7989	0.0320	24.99	0.000
ETH,XRP	0.7689	0.0358	21.50	0.000
ETH,EOS	0.7096	0.0431	16.48	0.000
ETH,NEO	0.7067	0.0430	16.43	0.000
ETH,Alts	0.8934	0.0182	49.05	0.000
LTC,XRP	0.6694	0.0486	13.76	0.000
LTC,EOS	0.6465	0.0494	13.08	0.000
LTC,NEO	0.6035	0.0550	10.97	0.000
LTC,Alts	0.8239	0.0285	28.89	0.000
XRP,EOS	0.6147	0.0544	11.29	0.000
XRP,NEO	0.5517	0.0576	9.58	0.000
XRP,Alts	0.7750	0.0356	21.75	0.000
EOS,NEO	0.5946	0.0576	10.32	0.000
EOS,Alts	0.7108	0.0442	16.06	0.000
NEO,Alts	0.7162	0.0424	16.90	0.000
$\boldsymbol{\lambda_1}$	0.2177	0.0288	7.56	0.000
$\boldsymbol{\lambda_2}$	0.5268	0.0665	8.54	0.000

Table 9: Stata output of MGARCH regression of the cryptocurrency class. The table presents the correlation-parameters for every combination. Furthermore, it shows the lambda-parameters of both the ARCH- and the GARCH-term.

The table shows that the all the correlations vary between 0.5517 (the lowest value) and 0.8934 (the highest value). Next to that, these coefficients are all statistically significant at a 1-percent level and are therefore relevant to interpret. For example, the correlation between Bitcoin and Ethereum is 0.7596. This indicates that a one unit increase in the variance of Bitcoin leads to the following increase in the variance of Ethereum:

$$\rho_{BTC,ETH} * \left(\frac{\gamma_{0,BTC}}{1-(\gamma_{1,BTC}+\delta_{1,BTC})}\right) / \left(\frac{\gamma_{0,ETH}}{1-(\gamma_{1,ETH}+\delta_{1,ETH})}\right)$$
$$=$$
$$0.7596 * \left(\frac{0.0006}{1-(0.5509+0.3283)}\right) / \left(\frac{0.0007}{1-(0.6048+0.2972)}\right)$$
$$=$$
$$0.5282$$

However, note that the regression is modelling multiple return variables altogether. Therefore, there is presence of inter-correlation in this model, meaning that there are mutual connections between the variables. Thus, a one unit increase in the variance of Bitcoin does not necessarily lead to an increase in the variance of Ethereum of 0.5282, since other factors have an impact on the variance as well. Hence, quantifying the effect is extremely complex. All the constant-terms, ARCH-terms, GARCH-terms, and correlation-terms have an impact on the exact effect. Nevertheless, the coefficients do provide information about the strength of the correlations between each pair of variables.

Next to that, the table shows that both the lambda parameters are statistically significant and that the parameter λ_1 is lower than the parameter λ_2. This indicates that in the case of cryptocurrencies, the one-period lagged values of the variance have more importance than the one-period lagged residuals. Nonetheless, both the effect are relevant due to the significant level of the parameters. Hence, both the one-period lagged residuals and the one-period lagged variances have an effect on the variance today. Furthermore, the summation of both parameters is less than 1. This implies that there is mean reversion, meaning that shocks in the variance are not permanent over time.

Once again, it is a relative concept to state whether or not these effects are strong compared to other asset/currency classes. Therefore, a comparison is made in the next paragraph to investigate the strength of these effects.

IV.II Results comparison

The Table below presents the comparison of the three classes included in this research. All coefficients included in this table are statistically significant at a 10-percent level or higher.

		Cryptocurrencies	Fiat currencies	Indices
γ_0	Average	**0.0011**	**0.0000**	**0.0000**
	Highest	0.0028	0.0000	0.0000
	Lowest	0.0005	0.0000	0.0000
γ_1	Average	**0.6516**	**0.4373**	**0.2480**
	Highest	1.1691	0.9791	0.4880
	Lowest	0.4254	0.2128	0.1276
δ_1	Average	**0.4064**	**0.2024**	**0.6463**
	Highest	0.4996	0.6344	1.0379
	Lowest	0.2972	-0.2120	0.0841
ρ	Average	**0.7060**	**0.2958**	**0.4901**
	Highest	0.8934	0.5956	0.9251
	Lowest	0.5517	-0.0687	0.1835
λ_1	Value	**0.2177**	**0.1359**	**0.0237**
λ_2	Value	**0.5268**	**0.3103**	**0.4959**

Table 10: Presentation of the comparison between the coefficients of all three MGARCH regressions. Hence, the results of the cryptocurrencies, fiat currencies, and the indices are compared. For each parameter, the average value, highest individual value, and the lowest individual value is presented. In this comparison, all coefficients that are insignificant at a 10-percent level or higher (>0.10) are excluded. Furthermore, values lower than 0.00005 are presented as being equal to '0.0000'. Logically, in reality, the value of a variance is not exactly equal to 0.

Multiple aspects can be derived from the coefficients in the table. The results are described below for each parameter individually. The complete Stata outputs of both the fiat currency regression and the indices regression are presented in Appendix 1 to 4.

- $\boldsymbol{\gamma_0}$ (=constant terms): The only average constant term that is presented to be higher than 0 is the one of the cryptocurrency regression. This indicates that the long-run average variance of cryptocurrencies is higher than those of the other two classes. Moreover, all the individual constant terms of the fiat regression and the index regression are close to 0. Hence, all the constant terms of cryptocurrencies do have a higher value than any other constant term in the fiat regression and index regression. As the table presents, the lowest constant term within the cryptocurrency regression has a value of 0.0005.

- $\boldsymbol{\gamma_1}$ (=ARCH parameters): Results in the table clearly indicate that past shocks in the variance of cryptocurrencies have the strongest effect on the current period's variance. The average ARCH-parameter in this regression is 0.6516, whereas the ARCH-parameter is 0.4373 for the fiat regression and 0.2480 for the index regression.

  Hence, as expected, lagged residuals have the strongest effect on the variance in the cryptocurrency market. This was expected since these are relatively new and unstable currencies. Thus, a shock in the variance causes more uncertainty about the actual value than in the case of fiat currencies or indices. This may also explain why the average ARCH-parameter for the indices is the lowest since indices are based on stocks of companies, which have an actual fundamental value. Meaning there more certainty about the actual value of the underlying asset.

- $\boldsymbol{\delta_1}$ (=GARCH parameters): The table shows the highest value of the GARCH-parameter in the index regression (0.6463). Thus, the ARCH effect is weaker compared to the cryptocurrencies and the fiat currencies (see ARCH parameter) but the effect lasts longer. Meaning that the volatility of indices is more persistent than those of the other two asset classes.

  This may be explained due to shocks occurring on a macroeconomic scale. Worldwide, multiple factors can lead to economic circumstances of crisis. Overall, these are circumstances that are not easily solved since crises usually last for multiple years (Korotayev & Tsirel, 2010). An economic crisis has (on average) a negative impact on the value companies. It creates uncertainty about the value and continuation of companies, undermining the fundamental value (Campello et al., 2011). Since these crises can last for a longer period of time, it could explain why the volatility of indices is more persistent over time than those of the other two classes.

- $\boldsymbol{\rho_{yz}}$ (=correlation parameters): The correlation parameter in the cryptocurrency regression is relatively high compared to the other two asset classes. This is in line with the expectations of this research for the same reason as mentioned in the paragraph of the ARCH parameter. At first, the correlation is high due to the strong influence of Bitcoin on the altcoins (Cizek, 2015). Secondly, this was expected because the market is relatively new and unstable. Meaning that the market as a whole is more sensitive to shocks in the variance. The cryptocurrencies are more likely to jointly increase (decrease) in value if good (bad) news arises about the market for cryptocurrencies.

  Furthermore, the coefficients for the fiat regression and the index regression are also quite different (0.2958 and 0.4901 respectively). The fact that the average correlation between the indices is higher could again be explained due to economic circumstances. As a result of bullish (bearish) periods, indices tend to increase (decrease) in value on an average basis. Nevertheless, the average correlation between cryptocurrencies is clearly the highest of the three classes.

- λ_1 (=lambda-1 parameters): The slowest decay for the ARCH-effect occurs at the cryptocurrency class. Once again, this is in line with expectations because the uncertainty in this market is likely to be high since it is relatively new and unstable. In case of the index regression, this parameter is so low that it is negligible. Hence, the ARCH-effect is not only weak (compared to the other two classes), but it is also rapidly declining over time.

- λ_2 (=lambda-2 parameters): Notable is that all three parameters are higher than the lambda 1 parameter within the same class. Hence, the GARCH-effect has a slower decay over time compared to the ARCH-effect. Meaning that the lagged values of the variance have more importance than the lagged values of the residuals.

  Furthermore, the table shows that the lambda 2 parameter of the cryptocurrency regression is the highest. Thus, the slowest decay of the GARCH-effect occurs in the cryptocurrency class. Next to that, note that the lambda 2 coefficient in the index regression is nearly equal to the coefficient of the cryptocurrencies. This indicates that the indices both have a strong GARCH-effect and one that is quite persistent over time since the coefficient is (for example) higher than those of the fiat currencies.

The graphs below present the conditional volatility over time of the Euro (=fiat currency) and the Dow Jones Industrial Average (=index), to make a visual comparison of the three classes as well. The conditional volatility graphs of the other five fiat currencies and indices are presented in Appendix 5 and Appendix 6 respectively. Hence, for this comparison, the graph of the Euro represents the fiat currencies and the graph of the Dow Jones represents the indices.

Results in the Appendix indicate that these are both good representatives for the two classes. Meaning that the height and persistence of the volatility is (relatively) similar within these two classes when comparing it to the cryptocurrencies. Note that (for this comparison) the graphs of the conditional volatility of Bitcoin and Litecoin are already mentioned in the previous paragraph.

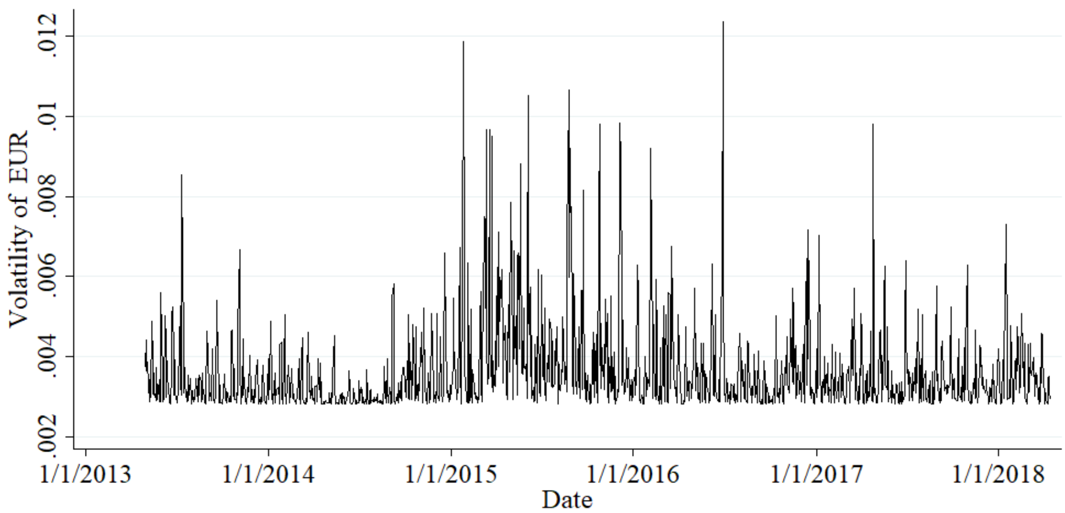

Figure 5: Daily volatility (square root of the conditional variance) of the Euro. This filtered volatility of the Euro is obtained after running the MGARCH model solely for this fiat currency. Afterward, Stata predicted these values for the conditional daily volatility.

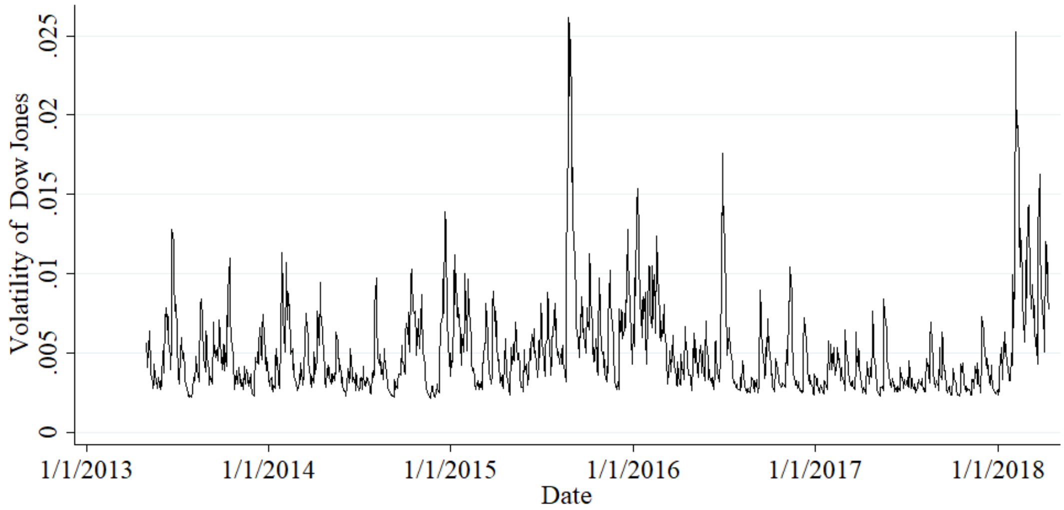

Figure 6: Daily volatility (square root of the conditional variance) of the Dow Jones Industrial Average index. This filtered volatility of the Dow Jones is obtained after running the MGARCH model solely for this index. Afterward, Stata predicted these values for the conditional daily volatility.

At first, the levels of daily volatility on the y-axis indicate immense differences in terms of the height of the volatility. The daily volatility levels of Bitcoin and Litecoin vary (approximately) between 2% and 20% (with outliers up to 30%). As a comparison, fiat currencies and indices show daily volatility levels of roughly 0.3% to 3%.

Secondly, the graphs of Bitcoin, Litecoin, and the Dow Jones seem to visualize a stronger persistence of volatility clustering than the graph of the Euro. For the two cryptocurrencies, this is especially the case during late 2013 and late 2017. In these periods, the two cryptocurrencies were outstandingly volatile with a high persistence in this effect as well. Additionally, the graph of the Dow Jones shows multiple periods in which there is persistence in the clustering of high volatility levels. Hence, the graphs seem to suggest that the comparison (of the quantified results) in table 10 is correct.

V. Conclusion

This research sought to identify how the past values of the variance of cryptocurrencies impact the present value of this variance in terms of strength and persistence. Furthermore, to put this analysis into perspective, these results were compared to this same effect for fiat currencies and indices.

This study revealed that in the case of cryptocurrencies, the lagged values of the variance have a relatively strong impact on the current variance, compared to the others two classes. The impact is respectively about 50% and 160% stronger compared to fiat currencies and indices, based on a comparison of the coefficients. Furthermore, the decay of this effect is the slowest in the case of cryptocurrencies. Hence, the effect persists longer over time compared to the other two asset classes.

Secondly, this study affirms that changes in the variance of cryptocurrencies affect future variances for a longer period of time compared to this same analysis for fiat currencies. However, the persistence of the variance is even stronger in the case of indices. This can be economically explained since economic crises last relatively long and these events have a negative impact on the fundamental values of companies and on the indices. Thus, this strengthens the effect of the lagged variance influencing the current variance for a longer period of time. The visualized comparison of the volatility graphs seem to confirm this effect.

Additionally, the correlation between cryptocurrencies is found to be substantially larger than those between fiat currencies and indices (values of 0.71, 0.30, and 0.49, respectively). Hence, the co-movement within this class is substantially larger. Meaning that the effects mentioned above are more likely to be present in other cryptocurrencies as well. This is indicated by the relatively high correlation. Thus, the behavior of the variance of any random cryptocurrency is likely to show the same effects as the cryptocurrencies that are analyzed in this research.

Finally, the results show that for fiat currencies and indices, the sum of the ARCH-parameter and the GARCH-parameter is, on average, lower than 1 ($\gamma_1 + \delta_1 < 1$). Meaning that there is presence of mean reversion in the variance. However, in the case of cryptocurrencies, the sum of the two parameters is, above $1(\gamma_1 + \delta_1 > 1)$. Thus, on average, the variance of cryptocurrencies is unstable since there is an exploding variance forecast (Rizvi and Arshad, 2013). Nonetheless, when analyzing the individual results, only Ripple and EOS show this effect. Therefore it is concluded that cryptocurrencies do not necessarily have an exploding variance forecast, but on average tend to act more like having an unstable variance.

VI. Recommendations and limitations

Based on the results of this research and the final conclusion, multiple recommendations can be drawn for various parties.

For academics, this research can be considered the groundwork and motive for further studying the behavior of the variance of cryptocurrencies. Suggestions for further research could be the studying of the behavior of the variance in certain time periods, for example, in an event study. If solely data is obtained in periods of crisis, results for all three classes may differ substantially. Next to that, further research could cover the comparison to other asset classes. For example, comparing the behavior of the variance of cryptocurrencies to the behavior of the variance of bonds, commodities, or real estate.

In this research, quantified evidence is provided that the variance does behave differently compared to other markets. It is relevant to further examine the variance because the total market capitalization has had an exponential increase since the origination of the market. Therefore, it is hard to get an understanding of the risk of this increasing sum of money. Hence, to academics, it is solely recommended to further investigate the behavior of the variance to obtain a good understanding of this concept.

Secondly, to make clear judgments about the market, it is recommended for governmental institutions to examine all relevant (future) research on the subject. Academic papers can substantiate political decisions by providing relevant information about the behavior of the market. For example, this research provides knowledge about the reaction of the variance of the cryptocurrencies compared to two other ‘asset’ classes. Based on these results, governmental institutions could strengthen regulations to protect investors from devoting too much money to cryptocurrencies. Hence, by using all relevant academic research in a suitable way, institutions can protect investors in volatile economic periods by putting the right policies in place.

Thirdly, it is recommended for investors to be attentive for outbreaks of volatile periods since this research has shown that these periods can be quite persistent relative to the other two asset classes. Moreover, the results show an exploding variance forecast. Meaning that the variance does not necessarily move towards a mean over a longer period of time. This indicates that investors face an increased level of risk when the variance starts to increase over time. Thus, investors should individually prefer a certain level of risk and stop to hold on to cryptocurrencies when certain volatile periods arise that exceed the maximum desired level of risk.

Finally, this research also has its limitations. For instance, in the period of executing this research, data of cryptocurrencies is only available for approximately five years. Meaning that the market is relatively new compared to (for example) the market for equities and fiat currencies. Hence, since the market is relatively new, the behavior (of the variance) may change in the upcoming years. Therefore, the conclusions of this research can become irrelevant in terms of using them to explain the behavior of the variance in (distant) future periods. Over a certain amount of years, a more comprehensive research can be executed, especially because results can be compared within multiple periods of economic prosperity and economic downturn.

Another limitation is that the MGARCH model is executed with only one lag for every parameter. However, Stata is not able to run the same model with more than one lag, since too many iterations are needed to obtain an output in Stata. Nevertheless, a relevant extension of this research would be to use more cryptocurrencies or more quantities of any asset class in the dataset. Thus, this research is limited in the number of cryptocurrencies used. An increase in the dataset provides the possibility to run more divergent regressions and hence, examine more relations between/within several asset classes. An increase in the dataset could both be in terms of increasing the amount of daily data, or an increase in the number of cryptocurrencies included in the dataset.

Interest in multiple (and more extensive) comparisons can be due to any reason in a logical economic context. For example, future studies could indicate that cryptocurrencies are becoming a substitutional investment for derivatives. In that case, a comparison between the price and/or variance developments of the two would be interesting material to investigate. Hence, the limitation of this research is that little research is executed about cryptocurrencies. Therefore, it is challenging to determine the most applicable issue to investigate within this interesting new market.

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VIII. Appendix

Appendices are presented at each page individually.

VIII.I Appendix 1

MGARCH - fiat currencies		γ_0	γ_1	δ_1
EUR	Coef.	0.0000	**0.3643**	**0.1197**
	Std. Err.	0.0000	0.0400	0.0639
	z	8.42	9.11	1.87
	P>z	0.000	0.000	0.061
GBP	Coef.	0.0000	**0.9791**	**0.1305**
	Std. Err.	0.0000	0.0884	0.0452
	z	6.72	11.08	2.89
	P>z	0.000	0.000	0.004
AUD	Coef.	0.0000	**0.2328**	**0.6344**
	Std. Err.	0.0000	0.0362	0.1314
	z	1.19	6.44	4.83
	P>z	0.236	0.000	0.000
JPY	Coef.	0.0000	**0.3528**	**0.3930**
	Std. Err.	0.0000	0.0448	0.1065
	z	2.91	7.88	3.69
	P>z	0.004	0.000	0.000
CAD	Coef.	0.0000	**0.2128**	**-0.2120**
	Std. Err.	0.0000	0.0332	0.0669
	z	10.30	6.42	-3.17
	P>z	0.000	0.000	0.002
CHF	Coef.	0.0000	**0.4818**	**0.1487**
	Std. Err.	0.0000	0.0416	0.0503
	z	7.07	11.58	2.96
	P>z	0.000	0.000	0.003

Table 11: Stata output of MGARCH regression of the fiat currencies. The table presents the constant, the ARCH-parameter, and the GARCH-parameter for every fiat currency. For every parameter and every portfolio, the regression coefficient, the standard error, the z-value, and the 'P>z' value (a measure of significance) are presented.

VIII.II Appendix 2

MGARCH - fiat currencies				
ρ	Coef.	Std. Err.	z	P>z
EUR,GBP	0.5353	0.0247	21.63	0.000
EUR,AUD	0.4452	0.0270	16.49	0.000
EUR,JPY	0.4583	0.0264	17.35	0.000
EUR,CAD	0.4075	0.0280	14.56	0.000
EUR,CHF	-0.0687	0.0336	-2.04	0.041
GBP,AUD	0.3848	0.0298	12.92	0.000
GBP,JPY	0.2884	0.0332	8.69	0.000
GBP,CAD	0.3616	0.0304	11.89	0.000
GBP,CHF	-0.0033	0.0359	-0.09	0.926
AUD,JPY	0.3149	0.0307	10.26	0.000
AUD,CAD	0.5956	0.0211	28.20	0.000
AUD,CHF	-0.0573	0.0339	-1.69	0.091
JPY,CAD	0.2360	0.0321	7.34	0.000
JPY,CHF	-0.0314	0.0339	-0.93	0.354
CAD,CHF	-0.0568	0.0339	-1.68	0.093
λ_1	0.1359	0.0114	11.92	0.000
λ_2	0.3103	0.0613	5.06	0.000

Table 12: Stata output of MGARCH regression of the fiat currencies. The table presents the correlation-parameters for every combination. Furthermore, it shows the lambda-parameters of both the ARCH- and the GARCH-term.

VIII.III Appendix 3

MGARCH - indices		γ_0	γ_1	δ_1
USA	Coef.	0.0000	**0.2458**	**0.7558**
	Std. Err.	0.0000	0.0373	0.0881
	z	0.18	6.59	8.58
	P>z	0.856	0.000	0.000
CHN	Coef.	0.0000	**0.4880**	**0.4588**
	Std. Err.	0.0000	0.0548	0.0491
	z	2.37	8.91	9.34
	P>z	0.018	0.000	0.000
JPN	Coef.	0.0000	**0.1681**	**0.08412**
	Std. Err.	0.0000	0.0337	0.1305
	z	-0.02	4.99	6.45
	P>z	0.988	0.000	0.000
GER	Coef.	0.0000	**0.1276**	**1.0379**
	Std. Err.	0.0000	0.0235	0.1079
	z	-1.69	5.43	9.62
	P>z	0.091	0.000	0.000
FRA	Coef.	0.0000	**0.1461**	**0.9731**
	Std. Err.	0.0000	0.0243	0.0957
	z	-1.33	6.01	10.17
	P>z	0.184	0.000	0.000
ENG	Coef.	0.0000	**0.3123**	**0.5683**
	Std. Err.	0.0000	0.0385	0.0799
	z	2.14	8.11	7.12
	P>z	0.032	0.000	0.000

Table 13: Stata output of MGARCH regression of the indices. The table presents the constant, the ARCH-parameter, and the GARCH-parameter for every index. For every parameter and every portfolio, the regression coefficient, the standard error, the z-value, and the 'P>z' value (a measure of significance) are presented.

VIII.IV Appendix 4

MGARCH - indices ρ	Coef.	Std. Err.	z	P>z
EUR,GBP	0.1852	0.0294	6.31	0.000
EUR,AUD	0.4776	0.0229	20.81	0.000
EUR,JPY	0.6421	0.0168	38.19	0.000
EUR,CAD	0.6595	0.0162	40.71	0.000
EUR,CHF	0.6217	0.0179	34.64	0.000
GBP,AUD	0.2311	0.0281	8.23	0.000
GBP,JPY	0.1835	0.0291	6.30	0.000
GBP,CAD	0.1957	0.0291	6.73	0.000
GBP,CHF	0.2055	0.0288	7.13	0.000
AUD,JPY	0.5309	0.0207	25.67	0.000
AUD,CAD	0.5420	0.0205	26.42	0.000
AUD,CHF	0.5103	0.0217	23.49	0.000
JPY,CAD	0.9251	0.0039	237.10	0.000
JPY,CHF	0.7011	0.0147	47.69	0.000
CAD,CHF	0.7398	0.0133	55.81	0.000
λ_1	0.0237	0.0053	4.43	0.000
λ_2	0.4959	0.1519	3.27	0.001

Table 14: Stata output of MGARCH regression of the indices. The table presents the correlation-parameters for every combination. Furthermore, it shows the lambda-parameters of both the ARCH- and the GARCH-term.

VIII.V Appendix 5

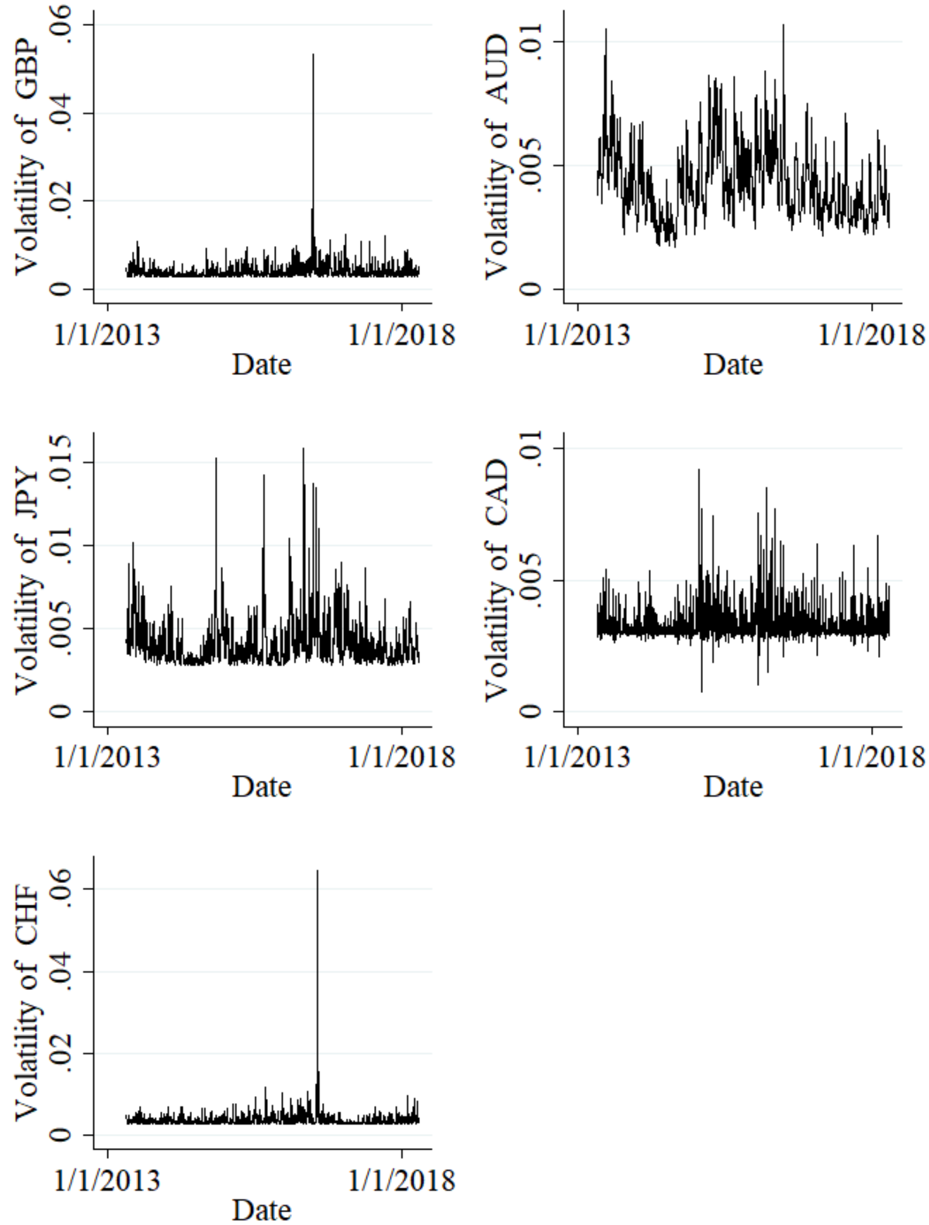

Figure 7: Daily volatilities (the square root of the conditional variances) of all the fiat currencies, except for the Euro. This filtered volatilities of the fiat currencies are obtained after running the MGARCH model solely for each currency individual. Afterward, Stata predicted these values for the conditional daily volatilities.

VIII.VI Appendix 6

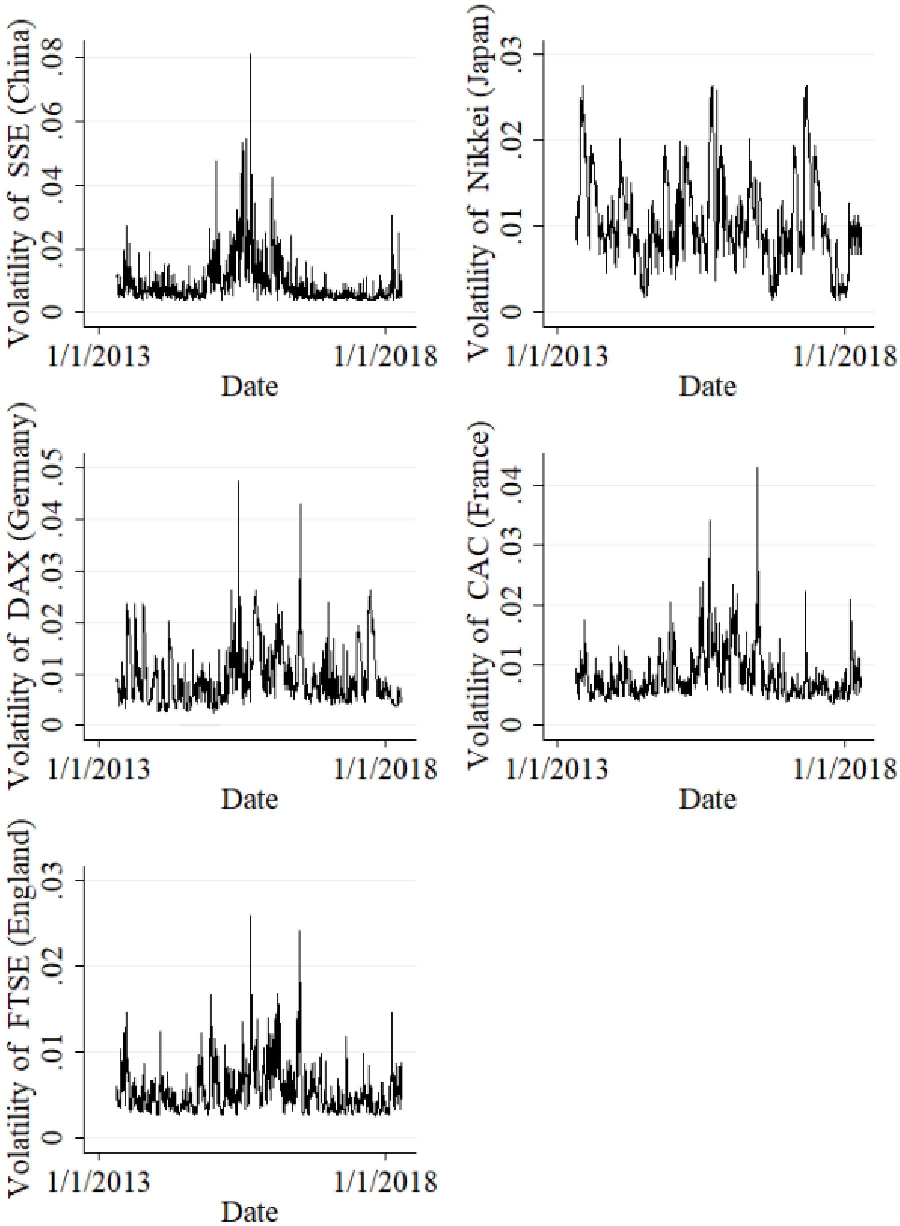

Figure 8: Daily volatilities (the square root of the conditional variances) of all the indices, except for the Dow Jones. This filtered volatilities of the indices are obtained after running the MGARCH model solely for each index individual. Afterward, Stata predicted these values for the conditional daily volatilities.