ISCTE IUL
Instituto Universitário de Lisboa

THE MACROECONOMIC DETERMINANTS OF CRYPTOCURRENCIES' RETURNS

Jan Janicki

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SUPERVISOR:
Prof. Alexandra Ferreira-Lopes, Assistant Professor, ISCTE Business School, Department of Economics

CO-SUPERVISOR:
Prof. Luís Filipe Martins, Assistant Professor with Habilitation, ISCTE Business School, Department of Economics

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Resumo

O objetivo desta tese é encontrar as determinantes que afetam os preços das criptomoedas. Foram estudadas as quatro principais criptomoedas e suas determinantes, de acordo com a literatura, usando-se dados entre os anos de 2013 e 2018. Especificamente, usaram-se variáveis diretamente relacionadas com as criptomoedas, tal como volume de transacções, e variáveis relacionadas com o ambiente financeiro e económico, tal como o índice SP500. Utilizando-se especificações do tipo ARCH, estimaram-se cinco modelos – dois para Bitcoin usando dois tipos diferentes de modelos ARCH, e um para cada uma das outras três moedas, as quais podem ser denominadas *altcoins* (moedas alternativas ao Bitcoin). Foram encontradas relações significativas entre as determinantes identificadas pela recente literatura na área, por exemplo o dólar Americano, o Euro, o ouro, a prata, retornos dos mercados financeiros, e características dos mercados das criptomoedas em estudo. Em particular, concluiu-se que os retornos do dólar têm sempre uma relação negativa com os retornos das criptomoedas e que o valor das transações têm sempre uma relação positiva com os retornos das criptomoedas. Outros determinantes têm diferentes impactos (positivos ou negativos) dependendo da criptomoeda em análise.

Palavras-Chave: Bitcoin, Ethereum, Litecoin, Ripple, cripto-moedas, determinantes do preço das cripto-moedas, determinantes da procura de ativos financeiros, modelos ARCH e seus derivados.

Códigos JEL: C58, G11, G12, G14

Abstract

The purpose of this dissertation is to find determinants affecting the cryptocurrencies prices. We use the four main cryptocurrencies and their main determinants, according to the literature, using data between the years of 2013 and 2018. Specifically, we use variables directly related with cryptocurrencies, like generated cryptocurrencies, and variables related with the financial and economic environment, like the SP 500 index. By using ARCH-type specifications we estimated five models – two for Bitcoin using two different types of ARCH models, and one for each of three other coins, which are called altcoins (alternative coins for Bitcoin). We found significant relationships between the determinants uncovered by the recent literature on the subject, for example the USA dollar, the Eurozone Euro, gold, silver, returns in financial markets, and characteristics of cryptocurrencies markets and the four cryptocurrencies in study. In particular, we found that returns of the dollar have always a negative relationship with the returns of each cryptocurrencies and the dollar value of daily transactions has always a positive relationship with the returns of each cryptocurrency. Other determinants have different impacts (either negative or positive) depending on the analyzed cryptocurrency.

Keywords**:** Bitcoin, Ethereum, Litecoin, Ripple, cryptocurrencies, price determinants of cryptocurrencies, determinants of the demand for assets, ARCH-type models.

JEL Codes**:** C58, G11, G12, G14

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List of Abbreviations

ADL - Autoregressive Distributed Lag

API - Application Programming Interface

AR-CGARCH – Autoregressive – Component Generalized Autoregressive Conditional Heteroscedasticity

BGS-VAR - Bitgrail Shares - Vector Autoregression

BTC - Bitcoin

CMA - Comparative Market Analysis

CNY – Chinese Yuan

DCC – Dynamic Conditional Correlation

DFA - Detrended Fluctuation Analysis

EPU – Economic Policy Uncertainty

ETH - Ethereum

EUR – Eurozone Euro

GARCH - Generalized Autoregressive Conditional Heteroscedasticity

GHSKT - Generalized Hyperbolic Skew Student's *t*

GPH - Geometric-Poisson Hybrid

LAD - Least Absolute Deviations

LS – Least Squares

LTC - Litecoin

MLE - Maximum Likelihood Estimator

OLS - Ordinary Least Squares

SP500 - Standard & Poor's 500

USD - United States Dollar

VAR - Vector Autoregression

VEC – Vector Error Correction

VIX - Volatility Index

XRP - Ripple

1. Introduction

This dissertation aims to check what macroeconomic variables determine cryptocurrencies returns, using the four most used cryptocurrencies – Bitcoin, Ethereum, Ripple, and Litecoin, with weekly data between the years of 2013 and 2018. Cryptocurrencies markets are very recent and literature about these markets is thriving, but is not consolidated yet.

This dissertation presents some new contributions to the literature. Unlike most of the research done so far, we will analyse, not one cryptocurrency individually, but four, which allows us to see if there are interactions effects between them. Secondly, our time span includes periods when a price bubble surged in the cryptocurrencies' market.

Using Autoregressive Conditional Heteroskedasticity (ARCH) type models, we estimated five models – two for Bitcoin using two different ARCH specifications, because this is the leading cryptocurrency, with most data available; and one for each of other three cryptocurrencies, which are called altcoins (alternative coins for Bitcoin). The results answered our research question – the determinants identified by the recent literature on cryptocurrencies – namely, gold, silver, the USA dollar (USD), the Eurozone Euro (EUR), and variables that characterize the cryptocurrencies markets, like number of generated currencies, volume of transactions, among others do in fact determine cryptocurrencies returns. Specifically, we found that the returns of the USD always have a negative relationship with the returns of the cryptocurrencies and the value of transactions always have a positive relationship with the returns of each cryptocurrency. The other determinants are also significant, but have positive or negative relationships, depending of the cryptocurrency in analysis.

This dissertation has the following structure. In Section 2 we make a literature review about the recent but very fruitful research on cryptocurrencies and its main topics of interest. Section 3 provides a quick look at the functioning of the cryptocurrency market. Section 4 presents information on data and methodological issues. In Section 5 we discuss the results and Section 6 concludes.

2. Literature Review

This section explores the most studied research questions about cryptocurrencies. From the analysed literature, we also have found the determinants that we used in our models for cryptocurrencies returns.

2.1 Bubbles on the Cryptocurrency Markets

Cryptocurrencies do not have only one price determinant, and additionally, cryptocurrency markets are significantly vulnerable to speculations. Speculations might cause bubbles on this market. If the cryptocurrency is popular than the chance of bubble to appear is higher, mostly because of global media. In this section, authors are investigating possibilities of bubbles in cryptocurrency markets.

Cheah and Fry (2015) investigate bubbles in Bitcoin markets. They are using the price (in USD) of Bitcoin taken from the Bitcoin Coindesk Index from 2010 until 2014. They use the cointegration Johansen test and found that Bitcoin is prone to speculative bubbles. Additionally, they also uncover that Bitcoin's fundamental value (the value of a currency determined through fundamental analysis without reference to its market value) is zero and that the bubble component (defined as the ‘‘average distance’’ between fundamental and bubble prices) contained within Bitcoin prices is substantial.

Corbet *et al.* (2017) analyse datestamping bubbles in Bitcoin and Ethereum market. They use the Application Programming Interface (API) data (in USD) for the period between 2009 and 2017 and the BADFS unit root Phillips methodology, which is a technique that has proven to be robust in detecting bubbles, to search for bubbles in both markets. The authors find that there are periods of clear bubble behaviour, with Bitcoin now almost certainly in a bubble phase.

2.2 Hedging Capabilities of Cryptocurrencies

In this section, researchers are answering the question if cryptocurrencies can be a good hedging tool. They are checking if people can store money in cryptocurrencies like they do with gold. Authors want to check if the price of cryptocurrencies is stable enough to be good hedging tool.

Bouri *et al.* (2017) analyse the (existence of the) safe heaven properties of Bitcoin, between 2011 and 2015. They use data for price index values for Bitcoin and other financial assets (stocks, bonds, currencies, and commodities), and by using Engle's bivariate Dynamic Conditional Correlation (DCC) model, the authors conclude that Bitcoin is a poor hedge and is suitable for diversification purposes only. However, Bitcoin has hedge and safe haven properties that differed between horizons/markets, e.g., it can be a safe haven against weekly extreme down movements in Asian stocks.

Bouri *et al.* (2017) analyse the question if Bitcoin had hedging properties against global uncertainty. They use data for the period between 2011 and 2016, taken from Coindesk (www.coindesk.com) for Bitcoin and from the DataStream of Thomson Reuters for the Volatility Index (VIX). The authors use the wavelet multiscale decomposition method and reveal that Bitcoin does act as a hedge against uncertainty: it reacts positively to uncertainty at both higher quantiles and shorter frequency movements of Bitcoin returns.

Demir *et al.* (2018) are interested about suggestions for economic policy regarding Bitcoin's return. They used Bitcoin data from 2010 until 2017 from Coindesk, as well as the daily Economic Policy Uncertainty (EPU) index in the USA and with the help of a Bitgrail shares in Vector Autoregression (BGS-VAR) model, they find that Bitcoin can serve as a hedging tool against uncertainty, and that Bitcoin returns are negatively associated with economic policy uncertainty.

Dyhberg (2018) investigates if Bitcoin is virtual gold, using daily observations of exchange rates and Financial Times Stock Exchange Index from Datastream, for the period between 2010 and 2015, and the Bitcoin price from Coindesk. The author uses the asymmetrical Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology and concludes that bitcoin and gold have similar hedging capabilities in the UK market and that hedging abilities of bitcoin against the US dollar are shorter lived than the hedging abilities of the gold against the US dollar.

2.3 Investing in the Cryptocurrency Market

Cryptocurrencies besides being alternative money might also be a good investing commodity due to their liquidity. On the other hand, they are very volatile, so it is as easy to win as to lose money. In this section, authors are checking if cryptocurrencies are worth investing or not.

Feng *et al.* (2017) analyse informed trading in the Bitcoin market, from 2011 until 2017, with data taken from bitcoincharts.com. These authors construct their own order-size based measure to detect informed trading and conclude that informed trading in the Bitcoin market suggests that people who get information before it is widely available, profit on their private information, at the cost of other market participants losses. Hence, the lack of clear regulatory laws and regulatory authorities are potential reasons for the existence of informed trading.

Brauneis and Mestel (2018) analyse cryptocurrencies' prices, using data from 2015 until 2017, provided by coinmarketcap.com. The authors concluded that cryptocurrencies become less predictable as liquidity increases and that the bid–ask spread shows the expected negative effect towards efficiency.

Corbet *et al.* (2018) explore dynamic relationships between cryptocurrencies and other financial assets, using data from CryproCompare.com for cryptocurrencies and Bloomberg for financial assets. They use the generalized variance decomposition methodology by Diebold and Yilmaz (2012) and conclude that cryptocurrencies may offer diversification benefits for investors with short investment horizons and that time variation in the linkages reflects external economic and financial shocks.

Gkillas and Katsiampa (2018) apply extreme value theory, a theory that tries to uncover the characteristics of the distribution tails of asset returns, to assess which cryptocurrency is the most and least risky. They used the five largest cryptocurrencies, each one from the earliest date available until 2017, taken from www.coindesk.com for Bitcoin and coinmarketcap.com for the remaining cryptocurrencies. They use the peaks-over-threshold, which is a method to extract extremes, and find that Bitcoin Cash is the riskiest cryptocurrency, while Bitcoin and Litecoin are the least risky cryptocurrencies in terms of investing.

Tiwari *et al.* (2018) use data for the period between 2010 and 2017, from www.coindesk.com, to study the efficiency of Bitcoin. The authors use the Detrended Fluctuation Analysis (DFA), the Comparative Market Analysis (CMA-1 and CMA-2), Periodogram-Least Absolute Deviations (LAD), Periodogram-Least Squares (LS), GPH, and the Maximum Likelihood Estimator (MLE) estimation techniques and reach the conclusion that the Bitcoin market is efficient with some exception to the period of April–August, 2013 and August–November, 2016.

Ciaian *et al.* (2018) investigate the virtual relationships between the Bitcoin and the Altcoin markets, which are markets for other cryptocurrencies which prices are correlated with the Bitcoin price. They use data on virtual currency supply and demand data from 2013 until 2016 for Bitcoin, 6 major Altcoins and 10 minor Altcoins, which they extract from quandl.com and coinmarketcap.com. Additionally, they also use for commodities like oil and gold, include two exchange rates for the USD/EUR and the CNY/USD. The authors use the Autoregressive Distributive Lag (ADL) model and conclude that the Bitcoin and the Altcoin markets are interdependent, the Bitcoin-Altcoin price relationship is significantly stronger in the short-run than in the long-run, and finally, in the long-run, macro-financial indicators determine the Altcoin price formation to a slightly greater degree than Bitcoin does.

2.4 Is Cryptocurrency Money?

Money is typically defined by economists as having three attributes: it functions as a medium of exchange, a unit of account, and a store of value. In this section researchers are trying to answer the question if cryptocurrencies can satisfy those three points.

Gervais *et al.* (2014) analyse if Bitcoin is a decentralized currency, i.e., there is no central entity or the administrator for the currency like a government or bank. They conclude that Bitcoin is not a "normal" currency, but it seems to be decentralized in a different way. Yermack (2015) tries to assess if Bitcoin is a real currency. The author concludes that Bitcoin fails to satisfy the criteria of fiat currencies and that Bitcoin appears to behave more like a speculative investment than a currency. Bjerg (2016) tries to explain how Bitcoin is money. As we know that fiat money must be used as a store of value, a medium of exchange, and a unit of account, the author conclude that Bitcoin is commodity money without gold, fiat money without a state, and credit money without debt. According to the author Bitcoin is something between money and a commodity, although closer to this last one.

2.5 What Determines Cryptocurrencies' Price?

Every currency or commodity has some variables that determine its price creation. Those prices can be driven for example by investors, difficulty of extracting, availability on the market. The same apply to cryptocurrencies. In this section researchers are searching for determinants affecting cryptocurrencies price.

Kristoufek (2015) assesses the main drivers of the Bitcoin price, by using data taken from www.coindesk.com for the Bitcoin price index and from www.blockchain.info for detailed series about Bitcoin markets. By using the wavelets methodology, the author finds that Bitcoin has standard fundamental factors—usage in trade, money supply, and price level and that those factors play a role in Bitcoin price over the long term. Secondly, the prices of Bitcoin are driven by investor's interest in the crypto-currency. Thirdly, that Bitcoin does not appear to be a safe haven investment.

Ciaian *et al.* (2016) analyse the economic determinants of Bitcoin's price formation. The authors use Bitcoin price denominated in USD, number of Bitcoin transactions *per* day, number of Bitcoin unique addresses, volume of daily Bitcoin views on Wikipedia, and also oil prices and stock market index as financial indicators for the period between 2009 until 2014. The authors use a Vector Autoregressive (VAR) model to find that Bitcoin market fundamentals and Bitcoin attractiveness for investors have a significant impact on Bitcoin price. However, their estimates do not support previous findings that the macro-financial developments are driving the Bitcoin price.

Hayes (2017) performs an empirical study in which the author researches the cryptocurrency value formation, using the cost of production model for valuing Bitcoin. In the study the author uses the total number of "coins' ever to be created, Bitcoin blocks, mining algorithms difficulty, and the market price for Bitcoin. By using the Ordinary Least Squares (OLS) regression estimator the author concludes that the main drivers of cryptocurrency value are: the level of competition in the network of producers, the rate of unit production, and the difficulty of the algorithm used to "mine" for the cryptocurrency.

Vieira (2017) does a deeper analysis of the formation of the Bitcoin price, including volatility and key drivers. The author gathers data on the Bitcoin price; the Standard & Poor 500 (SP500) index, the daily treasury real yield curve rates of "Treasury Inflation Protected Securities"; the daily USD price *per* ounce of gold; the daily number of confirmed Bitcoin transactions; the total number of unique addresses used on the Bitcoin blockchain; the total value of coinbase block rewards and transaction fees paid to miners, and the daily number of the term 'Bitcoin' queries made in Wikipedia. Data was obtained from several sources, namely: www.quandl.com, www.treasury.gov, and http://stats.grok.se. The author uses a GARCH-in-mean and a Vector Error Correction (VEC) models, to conclude that deviations above a long-run equilibrium for the Bitcoin price cause price decreases, that volatility can also have an effect on price formation (negative shocks have a stronger impact on volatility than positive ones), and that the number of transactions and the daily price of gold have a negative relationship with the Bitcoin price.

2.6 Volatility of the Cryptocurrency Market

In this section, academics will explore if Bitcoin behaves like a well-known financial asset or as something in between a commodity and a currency by analysing several aspects of its price volatility.

Dyhrberg (2016) explores the financial asset capabilities of Bitcoin using GARCH and exponential GARCH models. The author uses daily Bitcoin price data taken from the

Coindesk Price Index from 2010 to 2015, while all other daily variables used in this research were sourced from Datastream. The author concludes that gold is primarily used for its store of value' abilities and for its negative correlation with the USD, which makes it useful for hedging. However, these abilities are not certain for Bitcoin - when there are positive volatility shocks to the variables, with the exception of the dollar-euro exchange rate, the volatility of the returns on Bitcoin decrease.

Balcilar *et al.* (2017) are analysing if volume can predict Bitcoin returns and volatility. For this research they used two variables – the Bitcoin index and the trading volume. The daily price and volume data for Bitcoin traded on Bitstamp (the largest European Bitcoin exchange) were taken from www.bitcoincharts.com. The authors use the causality-in-quantiles test to reach the conclusion that volume can predict returns – except in the Bitcoin bear and bull market regimes and that volume cannot help predict the volatility of Bitcoin returns at any point of the conditional distribution.

Bariviera *et al.* (2017) uncover some stylized facts about the Bitcoin market, using daily data for Bitcoin downloaded from Datastream, for the period between 2011 and 2017. The authors estimated the Hurst Exponent, which is a measure of long-term memory of series, using the DFA method, and conclude that in spite of the fact that the Bitcoin presents large volatility, it is reducing over time. Moreover, the long-range memory of this cryptocurrency is not related to market liquidity.

Blau (2017) is trying to analyse price dynamics and speculative trading for the Bitcoin, using data from the Bitcoin Charts, which provides financial and technical data about the Bitcoin network, from 2010 until 2014. Additionally, the author also gathers historical exchange-rate data for 51 currencies, for the same period, from Bloomberg. Estimations using the GARCH model, do not find that speculative trading contributed to the unprecedented rise and subsequent crash in Bitcoin's value during 2013. However, speculative trading is directly associated with the Bitcoin's unusual level of volatility, due to the high liquidity of the Bitcoin market.

Catania and Grassi (2017) use data for the cryptocurrencies closing prices, taken from Coinmarketcup, while the standardized GHSKT and GARCH are used as estimation techniques. The authors concluded that differently from the exchange rate, the leverage effect has a substantial contribution to the volatility's dynamics and that a robust filter for extracting the volatility of cryptocurrencies' time–series is strongly required by the data.

Katsiampa (2017) analyses Bitcoin volatility, by using daily closing prices data taken from http://www.coindesk.com, for the Bitcoin Coindesk Index, from 2010 to 2016. The authors reach the conclusion that the conditional heteroscedasticity model can describe the Bitcoin price volatility better since its introduction (they use both GARCH and AR-CGARCH).

Baur *et al.* (2018) study the relationship between Bitcoin, gold, and the US dollar, using daily data taken from coindesk.com for the Bitcoin price and from Datastream for all other variables. The authors use GARCH to perform a volatility analysis and conclude that the Bitcoin exhibits distinctively different returns, volatility, and correlation characteristics when compared to gold and the US dollar.

3. Quick Look at the Cryptocurrency Market

The idea for the first cryptocurrency, the Bitcoin, appeared during the world financial crisis in 2008, and cryptocurrencies (crypto) originally were supposed to be an alternative for "normal" currencies, specially the USD.

The first cryptocurrency was the Bitcoin, but many others follow. Almost all prices of other cryptocurrencies nowadays are dependent on the Bitcoin price. They are called Altcoins (alternative coins). The main idea of the first cryptocurrencies were to be independent from governments and central banks, because these two institutions were main reason for world financial crisis in 2008 according to inventor of Bitcoin. This solution might have advantages like: transactions fees are small, it is anonymous, and it is fast and easy to set up. On the other hand, this anonymity might lead to the growth of the black market. Over time this idea evolved and now each cryptocurrency can have different purposes. For example, besides being an alternate source for money, some cryptocurrencies thrive to be typical investing commodities, or tokens, used inside virtual platforms.

Cryptocurrencies are designed to be self-contained for their value, with no need for banks to move and store the money. Prices are based on supply and demand, so the rate at which cryptocurrencies can be exchanged for another currency can fluctuate widely. For example, Bitcoin in December 2017 was worth $19,000 before decreasing to around $7,000 in the next few months. Prices are not rooted in any material goods. Some economists consider that the cost of producing cryptocurrency, which takes a large amount of electricity, is directly related to its market price. Once someone owns cryptocurrency, they behave like physical gold coins: they have value and can be traded just as if they were typical coins. People can use cryptocurrencies to purchase goods and services online, or store them and hope that their value increases over time. Cryptocurrencies are traded from one personal digital wallet to another. Wallet is a personal database that is stored on computer drive, on smartphone, tablet or somewhere in the cloud computing. Wallets are connected with the user by digital code, not by names of the people. New cryptocurrencies are made from solving complex mathematical task by miners - the huge network of people who contribute their personal computers to the network. They are auditing cryptocurrency transactions and keeping ledgers safe. Miners are paid for their work by earning new cryptocurrencies. Number of new cryptocurrencies which they get depends on complexity of the task. Cryptocurrencies hold a simple data ledger file called blockchain. Each blockchain is unique to each individual user and his personal wallet. All transactions are logged and available in a public ledger, helping ensure their authenticity and preventing fraud. There are some minor costs connected with using cryptocurrencies. Owners of some server nodes will charge one-time transaction fees every time person send money across their nodes and online exchanges will similarly charge when person cash cryptocurrencies in for dollars.

One of the most popular internet sites with information about cryptocurrencies are: www.coindesk.com, www.cryptonews.com and www.ccn.com. Those sites include information about most popular cryptocurrencies and also about new cryptocurrencies that have just appeared on the market or are going to do so. News on these sites include: market analysis, expert's opinions, price reports and more.

In our work we will use 4 cryptocurrencies, which are the most used cryptocurrencies. Firstly, we will use Bitcoin (BTC), which is the first and the most important cryptocurrency, covering about 30% of the whole market volume. Secondly, there will be the second biggest cryptocurrency – Ethereum (ETC). It covers about 20% of the market volume. This cryptocurrency is mainly used by programmers, which are using it to pay for services inside the Ethereum network. Thirdly, Litecoin (LTC) will be used. It covers about 10% of the market. In general, it was meant to be a cheaper version of Bitcoin. It is designed in almost the same way with only three minor changes – transactions are faster, maximum number of coins in the market is supposed to be higher, and transactions are safer. However, in spite of these advantages, it is still behind Bitcoin in terms of market share. Finally, we will use Ripple (XRP), which covers about 10% of the market and it was mainly designed for banks and private companies (for example, UniCredit, UBS, or Santander are using Ripple technology). Its goal is to give clients instantly and nearly free global financial transactions of any size with no chargebacks. The Ripple price is almost constant - about 0.50 USD for one XRP.

Following the above explanation, it can be stated that Litecoin is a perfect example of an Altcoin – very similar software and market specifics of the ones used by Bitcoin. Then there is Ethereum, which is a little bit different in its fundamentals than Bitcoin, but still its price depends in a significant proportion on the Bitcoin price. Finally, there is Ripple, which is different from the other cryptocurrencies mentioned above. It is quite stable in its prices, goals, and target market.

4. Data and Methodology

In this section, we present our database and our empirical methodology.

4.1 Data

In this sub-section we present the data. In bold you have the acronyms of the variables that we are going to use in the database. We also have information about the data sources and the time period.

The dependent variable is one of the following:

- **PRICEUSDBTC** - daily price in USD for Bitcoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **PRICEUSDETH** - daily price in USD for Ethereum, downloaded from www.coinmetrics.io (10.08.2015 - 02.05.2018)
- **PRICEUSDXRP -** daily price in USD for Ripple, downloaded from www.coinmetrics.io (07.08.2013 - 02.05.2018)
- **PRICEUSDLTC** - daily price in USD for Litecoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)

The list of regressors include:

- **USD** - daily nominal effective exchange rate of USD, downloaded from www.federalreserve.gov (01.05.2013 - 02.05.2018)
- **EUR** - daily nominal effective exchange rate of EUR, downloaded from www.ecb.europa.eu (01.05.2013 - 02.05.2018)
- **GOLD** - daily real effective price of gold, downloaded from www.investing.com (01.05.2013 - 02.05.2018)
- **SILVER** - daily real effective price of silver, downloaded from www.investing.com (01.05.2013 - 02.05.2018)

- **SP500** - data for the S&P500 index, downloaded from www.investing.com (01.05.2013 -02.05.2018)
- **TXVOLUMEUSDBTC** - on-chain daily transaction volume (how much value denominated in USD, circulates on the Bitcoin blockchain a day) for Bitcoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **TXVOLUMEUSDETH** - on-chain daily transaction volume (how much value denominated in USD, circulates on the Ethereum blockchain a day) for Ethereum, downloaded from www.coinmetrics.io (10.08.2015 - 02.05.2018)
- **TXVOLUMEUSDXRP** - on-chain daily transaction volume (how much value denominated in USD, circulates on the Ripple blockchain a day) for Ripple, downloaded from www.coinmetrics.io (07.08.2013 - 02.05.2018)
- **TXVOLUMEUSDLTC** - on-chain daily transaction volume (how much value denominated in USD, circulates on the Litecoin blockchain a day) for Litecoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **EXCHANGEVOLUMEUSDBTC** - daily exchange volume - (dollar value of the volume at exchanges like Bitfinex) for Bitcoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **EXCHANGEVOLUMEUSDETH** - daily exchange volume (dollar value of the volume at exchanges like Bitfinex) Ethereum, downloaded from www.coinmetrics.io (10.08.2015 - 02.05.2018)
- **EXCHANGEVOLUMEUSDXRP** - daily exchange volume (dollar value of the volume at exchanges like Bitfinex) Ripple, downloaded from www.coinmetrics.io (07.08.2013 - 02.05.2018)
- **EXCHANGEVOLUMEUSDLTC** - daily exchange volume (dollar value of the volume at exchanges like Bitfinex) Litecoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **GENERATEDCOINSBTC** - daily generated coins (number of new coins that have been brought into existence on that day) for Bitcoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)
- **GENERATEDCOINSETH -** daily generated coins (number of new coins that have been brought into existence on that day) for Ethereum, downloaded from www.coinmetrics.io (10.08.2015 - 02.05.2018)

- **GENERATEDCOINSXRP** - daily generated coins (number of new coins that have been brought into existence on that day) for Ripple, downloaded from www.coinmetrics.io (07.08.2013 - 02.05.2018)
- **GENERATEDCOINSLTC** - daily generated coins (number of new coins that have been brought into existence on that day) for Litecoin, downloaded from www.coinmetrics.io (01.05.2013 - 02.05.2018)

  Each one of the four **EXCHANGEVOLUMEUSD** variables is very similar to the correspondent **TXVOLUMEUSD.** The pairwise correlation is very large and therefore to avoid problems of collinearity we only use **TXVOLUMEUSD** in the models.

4.2 Methodology

In this section we explain the econometric methods that we use. Two different variations of the ARCH model are used in this dissertation. ARCH models are econometric models for time series data. They include a conditional variance equation for the model's error term. ARCH models are used in situations in which there might be periods of increased volatility. ARCH models are very useful in modelling financial time series data.

For the Bitcoin we have used both a Threshold Autoregressive Conditional Heteroskedasticity (TARCH) and an ARCH-in-mean models, because Bitcoin is the most complete cryptocurrency in terms of available data. For the ETH we have used the ARCH-in-mean, for the LTC the TARCH, and for the XPR, where the least amount of data was available, we have used ARCH. ARCH-in-mean and TARCH models were chosen, because those models are the most common tool used in modelling financial time series data, including cryptocurrencies, which are very volatile. We tried several other ARCH-type models but these seemed to be the best to fit the data. Using these models that are variance oriented, fits best in answering our research question. In a nutshell, the ARCH-in-mean includes the conditional variance to determine the expected mean of the variable of interest (i.e., the expected return is linked to the risk) and the TARCH model has asymmetric conditional variance in which during "bad times" (observed returns bellow its expected value) volatility is larger.

Besides the models' estimation we have run a few specification tests: Breusch-Pagan, Jarque-Bera and Ramsey RESET. The Breusch-Pagan test is used to test heteroscedasticity in linear regression models. The Jarque-Bera test checks if the sample data is normally distributed. The Ramsey RESET (Regression Equation Specification Error Test) checks whether the combination of explanatory variables fits in explaining the dependent variable in linear regression models.

Additionally, all variables were transformed into its weekly growth rates (log differences). The four currencies (BTC, ETH, LTC and XPR) are now measured as weekly returns (represented in the tables below by "ret", before each variable designation). The same applies to the five financial covariates (USD, EUR, Gold, Silver and SP500). Being in growth rates makes it easier to interpret (returns, regardless of the measurement units) and imposes stationarity in the variables. By the same reason (to guarantee stationarity) we also consider weekly growth rates for the Volume and Generated Coins ("pc" stands for percentage change). For some of the variables, we also have added one lag (a one period lag in the tables below is represented by L1, i.e., $L1_t$ should be read as t-1). Equation (1) shows the mean equation model we estimated to find the determinants for each cryptocurrency return:

$$ret\_i_t = \alpha_i + \beta_{1i}ret\_usd_t + \beta_{2i}ret\_usd\_L1_t + \beta_{3i}ret\_eur_t + \beta_{4i}ret\_eur\_L1_t + \beta_{5i}ret\_gold_t + \beta_{6i}ret\_gold\_L1_t + \beta_{7i}ret\_silver_t + \beta_{8i}ret\_silver\_L1_t + \beta_{9i}ret\_sp500_t + \beta_{10i}ret\_sp500\_L1_t + \beta_{11i}pc\_volume\_usd\_{i,t} + \beta_{12i}pc\_volume\_usd\_L1_{i,t} + \beta_{13i}pc\_generated\_coins\_{i,t} + \beta_{14i}pc\_generated\_coins\_L1_{i,t} + \epsilon_t \quad (1)$$

where i= btc, eth, ltc, and xpr and ϵ_t is the model's error term. Those coefficients that are found to be not statistical significant are dropped out of the final model.

5. Results

5.1 Bitcoin (BTC)

In order to assess which variables are more important to determine the returns of the Bitcoin, we estimate the model presented in equation (1), for which results are presented in Table 1.

As a result of the regression analysis, it is noted that all the predictive elements of the model proved to have a significant impact on the BTC returns. The coefficient for the returns of the USD, the Euro (lagged one week), the silver, the SP500 index lagged one week, and gold (also lagged one week) are negative, which seems to indicate that investors are treating bitcoin as a substitute for these financial assets. Silver has the highest negative impact on Bitcoin returns. The coefficient for the euro returns is positive, as well as the coefficient for the return of silver lagged one week. Euro returns (contemporaneous) have the highest positive impact on the Bitcoin return. The value (in dollars) of the BTC volume of transactions has a positive relationship with the BTC returns, i.e., higher value means higher returns, while the number of generated Bitcoins have a negative relationship, i.e., more bitcoins increases supply, decreases de return.

Table 1. Results of the ARCH-in-mean Model for the BTC Returns

Ret_btc	coef	std. Err.	Z	P>|z|	95% conf.	interval
Ret_usd	-1,12763	0,187035	-6,03	0,000	-1,49421	-0,76105
Ret_eur	4,012724	0,447918	8,96	0,000	3,134821	4,890627
Ret_eur_L1	-2,51434	0,512532	-4,91	0,000	-3,51888	-1,5098
Ret_silver	-0,80599	0,278323	-2,9	0,004	-1,35149	-0,26049
Ret_silver_L1	1,375536	0,275378	5	0,000	0,835805	1,915267
Ret_sp500_L1	-0,27422	0,069412	-3,95	0,000	-0,41027	-0,13818
Ret_gold_L1	-1,6993	0,21507	-7,9	0,000	-2,12083	-1,27778
Pc_volume_usd_btc_L1	0,065758	0,024875	2,64	0,008	0,017005	0,114511
Pc_generated_coins_btc	-0,06826	0,070266	-9,71	0,000	-0,82035	-0,54491
cons	-0,01154	0,007899	-2,46	0,144	-0,02703	0,003936
ARCHM (sigma2)	-0,0927	0,014489	-6,4	0,000	-0,1211	-0,06431
ARCH (L1)	2,274486	0,317073	7,17	0,000	1,653035	2,895937
cons	0,023588	0,004039	5,84	0,000	0,015671	0,031505

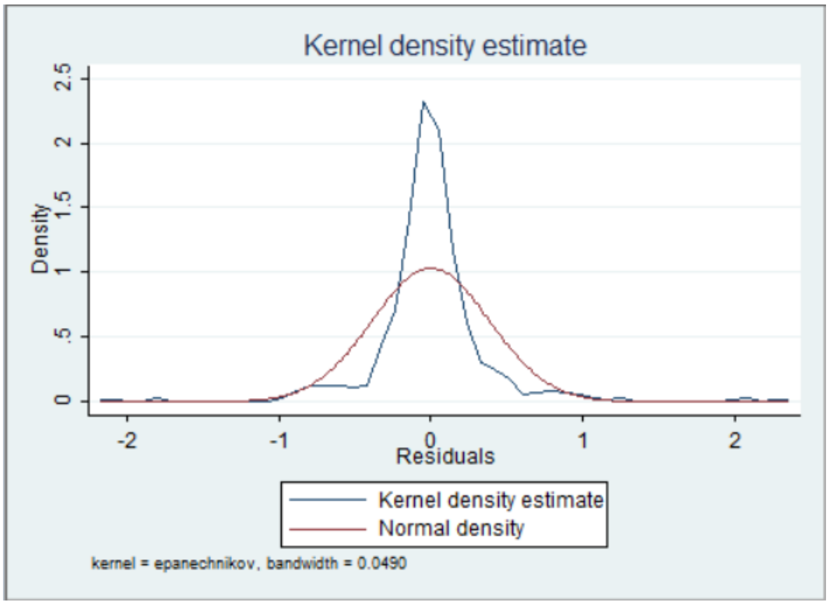

Figure 1. Kernel Density Estimation with Normal Density for the BTC model's residuals

Table 2. Normality Analysis of Residuals for the BTC

Skewness/Kurtosis test for normality					
		Pr	Pr	adj chi2	
Variable	Obs	(Skewness)	(Kurtosis)	(2)	Prob>chi2
e_norm	265	0,0007	0,0000	57,64	0,0000

As a result of the analysis of the residuals of our model in Table 2, we can verify that the residuals of the regression are not characterized by a distribution similar to the normal distribution, since p< 0.05. See also Figure 1.

Table 3. Ramsey Reset Test for the BTC

Ramsey Reset	
F (3,253)	20,72
Prob>F	0,0000

With the purpose of verifying the hypothesis of linearity of our model, the Ramsey Reset test was carried out, as we can see in Table 3. The results for the test, with a p<0.05, indicate an incorrect specification of the model.

The results of the tests for the normality of the residuals, and the Ramsey Reset test, indicate that the use of our model in equation (1), to assess the BTC returns' determinants, is not a good solution.

We also estimate equation (1) using a multiple regression model with TARCH effects. Results are in Table 4. As a result of the regression analysis, it is noted that all the predictive elements of the model proved to have a significant impact on BTC returns. The coefficients for the returns of the USD, returns of the euro (lagged one period), and returns of gold (lagged one period) are negative, expressing a negative relationship with the bitcoin returns. Gold has the highest negative impact on Bitcoin returns. The coefficient for the euro, silver (both contemporaneous and with a one-period lag), and SP500 index returns have a positive relationship with the BTC return. The euro returns have the highest positive impact on the Bitcoin returns. Like in the previous estimation, the BTC volume of transactions and the number of generated Bitcoins have the same signs.

Table 4. Multiple Regression Analysis and Results of TARCH Model for the BTC Returns

Ret_btc	Coef	std. Err.	Z	P>|z|	95% conf.	interval
Ret_usd	-0,33874	0,186724	-1,81	0,070	-0,70471	0,027228
Ret_eur	5,448173	0,428288	12,72	0,000	4,608744	6,287601
Ret_eur_L1	-1,90664	0,584519	-3,26	0,001	-3,05228	-0,76101
Ret_silver	0,795917	0,247269	3,22	0,001	0,311279	1,280554
Ret_silver_L1	0,993775	0,333309	2,98	0,003	0,340501	1,647049
Ret_sp500_L1	0,168417	0,05596	3,01	0,003	0,058738	0,278097
Ret_gold_L1	-2,28853	0,258103	-8,87	0,000	-2,7944	-1,78266
Pc_volume_usd_btc_L1	0,086375	0,036862	2,81	0,005	0,026231	0,146518
Pc_generated_coins_btc	-0,53378	0,070771	-7,34	0,000	-0,67641	-0,39115
cons	0,016387	0,016205	1,01	0,312	-0,01537	3,048147
ARCH (L1)	0,84488	0,243875	3,46	0,001	0,366894	1,322866
tarch (L1)	4,042375	0,96089	4,210	0,000	2,159065	5,925684
const	0,030342	0,003005	10,1	0,000	0,024451	0,036232

Table 5. Results of the Analysis of Homoscedasticity of the Random Components of the BTC for the TARCH Model

Breusch-Pagan	
chi2(7)	12,49
Prob>chi2	0,0856

Looking at the results of the Breusch-Pagan test, we can see that there are no grounds for rejecting the hypothesis of homoscedasticity of the random components. Therefore, the regression model predicting the BTC returns can be considered as correct.

5.2 Ethereum (ETH)

In order to assess which variables are more important to determine the returns of the Ethereum (ETH), we estimate the model presented in equation (1), for which results are presented in Table 6.

Table 6. Results for the ARCH-in-mean Model for the ETH Returns

Ret_eth	coef	std. Err.	z	P>|z|	95% conf.	interval
Ret_usd	-1,27773	0,091658	-13,94	0,000	-1,45737	-1,09808
Ret_eur	-1,46977	0,274606	-5,35	0,000	-2,00798	-0,93155
Ret_eur_L1	-4,38754	0,34234	-12,82	0,000	-5,05852	-3,71657
Ret_silver	0,841315	0,295671	2,85	0,004	0,261811	1,42082
Ret_silver_L1	-3,43375	0,21734	-15,8	0,000	-3,85973	-3,00777
Ret_sp500_L1	-1,34284	0,087689	-15,31	0,000	-1,5147	-1,17097
Ret_gold_L1	1,573281	0,178895	8,79	0,000	1,222653	1,923909
Pc_volume_usd_eth_L1	0,445316	0,005348	83,27	0,000	0,434834	0,455798
Pc_generated_coins_eth	-3,40892	0,145738	-23,39	0,000	-3,69456	-3,12328
cons	-0,14094	0,006589	-21,39	0,000	-0,15385	-0,12802
ARCHM (sigma2)	-0,00709	0,000598	-11,84	0,000	-0,00826	-0,00591
ARCH (L1)	14,06328	1,073624	13,1	0,000	11,95901	16,16754
cons	8,43E-06	0,000378	0,02	0,982	-0,00073	0,00075

As a result of the regression analysis, it is noted that all the predictive factors in the model proved to have a significant impact on the ETH returns. The coefficient for the returns of the USD, the euro (both contemporaneous and with the previous period), the silver (previous period), the SP500 index (previous period), have a negative relationship with the ETH returns. On the contrary, returns to silver (contemporaneous) and returns to gold (previous period) have a positive relationship. Returns of Gold have the highest positive impact on Ethereum returns. Like in the case of BTC, the ETH volume of transactions has a positive sign and the number of generated Ethereums have a negative sign.

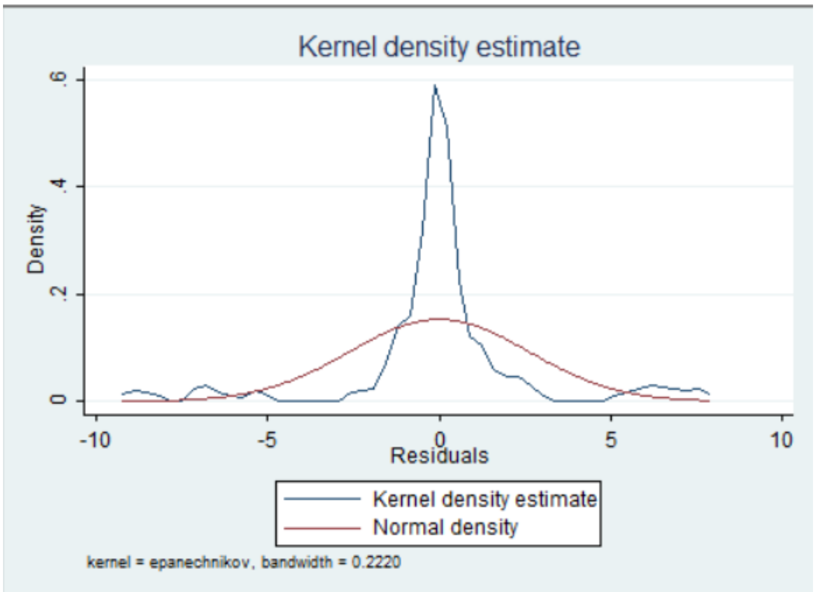

Figure 2. Kernel Density Estimation with Normal Density for the ETH model's residuals

Table 7. Normality Analysis of Residuals Distributions for the ETH

Skewness/Kurtosis test for normality					
		Pr	Pr	adj chi2	
Variable	Obs	(Skewness)	(Kurtosis)	(2)	Prob>chi2
e_norm	142	0,08	0,0000	18,35	0,0001

As we can see in Table 7, results for the normality of the residuals return a $p<0.05$, meaning that the residuals of the regression are not characterized by a distribution of results similar to the normal distribution. See also Figure 2.

Table 8. Results of the Analysis of Homoscedasticity of Random Components for the ETH

Breusch-Pagan	
F (7,130)	0,48
Prob>F	0,8464

As a result of the Breusch-Pagan test (Table 8), there are no grounds for rejecting the hypothesis of homoscedasticity of the random components. Therefore, the regression model predicting the ETH returns can be considered correct.

Table 9. Results of the Ramsey Reset Test for the ETH

Ramsey Reset	
F (3,127)	0,19
Prob>F	0,9001

In order to verify the hypothesis of the linearity of the model, the Ramsey Reset test was carried out in Table 9. The test results (p=0.9) indicate that the specification of the model is correct.

The conducted diagnosis of the model using the analysis of normality of residuals distribution, the homoscedasticity of the random component, and the Ramsey Reset test indicate, apart from the test to the normality of residuals distribution, that the use of the regression model to evaluate the ETH course is a correct solution.

5.3 Litecoin (LTC)

In order to assess which variables are more important to determine the returns of the Litecoin (LTC), we estimate the model presented in equation (1), for which results are presented in Table 10.

Table 10. Results for the ARCH Model for the LTC Returns

Ret_ltc	coef	std. Err.	z	P>|z|	95% conf.	interval
Ret_usd	-11,5492	2,378237	-4,86	0,000	-16,2105	-6,88793
Ret_silver_L1	5,700739	2,334655	2,44	0,015	1,124899	10,27658
Ret_sp500_L1	-1,4801	0,878069	-1,69	0,092	-3,20102	0,24083
Pc_volume_usd_ltc_L1	0,424143	0,111933	3,79	0,000	0,204759	0,643527
Pc_generated_coins_ltc	1,877943	0,488289	3,85	0,000	0,920914	2,834972
cons	0,327283	0,177603	1,84	0,065	-0,02081	0,675379
ARCH (L1)	0,050798	0,021451	2,37	0,018	0,008756	0,092841
tarch (L1)	2,629883	1,18916	2,21	0,027	0,299172	4,960594
const	4,077487	0,23206	17,57	0,000	3,622657	4,532317

As a result of the regression analysis, it is noted that all the predictive factors in the model proved to have a significant impact on the LTC returns. The coefficients for the returns of the USD and the SP500 index (of the previous period) exhibit a negative relationship with the LTC returns. The USD has the highest negative impact on the Litecoin returns. The coefficient for silver (lagged one week) shows a positive relationship with LTC returns. In terms of the characteristics of this cryptocurrency market, both the volume of transactions and the number of generated Litecoins have a positive relationship with the LTC returns.

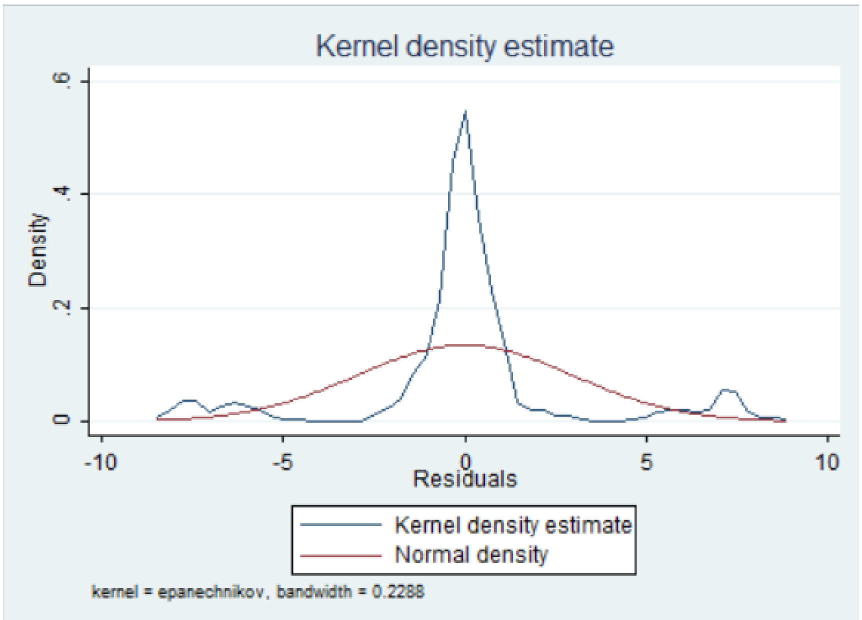

Figure 3. Kernel Density Estimation with Normal Density for the LTC model’s residuals

Table 11. Normality Analysis of Residuals Distributions for the LTC

Skewness/Kurtosis test for normality					
		Pr	Pr	adj chi2	
Variable	Obs	(Skewness)	(Kurtosis)	(2)	Prob>chi2
e_norm	265	0,8406	0,0000	16,47	0,0003

As a result of the analysis of Table 11, it is observed that the residuals of the regression are not characterized by a distribution of results similar to the normal distribution, since the p-value for the test is < 0.05. See also Figure 3.

Table 12. Results of the Analysis of Homoscedasticity of Random Components for the LTC

Breusch-Pagan	
chi2(7)	8,47
Prob>chi2	0,2931

The results of the Breusch-Pagan test in Table 12 state that there are no grounds for rejecting the hypothesis of homoscedasticity of the random components. Therefore, the model for the LTC can be considered correct.

Table 13. Ramsey Reset Test Results for the LTC

Ramsey Reset	
F (3,253)	0,15
Prob>F	0,9288

In order to verify the assessment of the linearity of the regression function, the Ramsey Reset test was carried out, for which we present results in Table 13. The obtained p-value for the test – 0.9 - indicate that we have used the correct specification for the model.

The conducted diagnosis of the model using the test for the normality of residuals distribution, the test for the homoscedasticity of the random components, and the Ramsey Reset test indicates (apart from the test to the normality of residuals distribution) that the use of the regression model to evaluate the LTC is a correct solution.

5.4 Ripple (XPR)

In order to assess which variables are more important to determine the returns of the Ripple (XPR), we estimate the model presented in equation (1), for which results are presented in Table 14.

As a result of the regression analysis, it is noted that all the predictive factors in the model proved to have a significant impact on the XPR returns. The coefficients for the returns of gold and silver (lagged one period) are negative, so for every unit increase in these variables, we expect a decrease in the Ripple returns, holding all other variables constant. The coefficient for the Euro (contemporaneous and in the previous period), silver (contemporaneous), the USD (lagged one period), and the SP500 index (lagged one period) are positive, i.e., for every unit increase in these variables, we expect an increase in the Ripple returns. The returns of the Euro have the highest positive impact on the Ripple return. Like for all other cryptocurrencies, the XPR volume of transactions has a positive relationship with the XPR returns.

Table 14. Results for the ARCH Model for the XPR Returns

Ret_xpr	coef	std. Err.	z	P>|z|	95% conf.	interval
Ret_usd_L1	0,779709	0,232919	3,35	0,001	0,323196	1,236223
Ret_eur	3,308971	0,778062	4,25	0,000	1,783998	4,833945
Ret_eur_L1	4,195827	0,810251	5,18	0,000	2,607765	5,78389
Ret_silver	0,953984	0,35014	2,72	0,006	0,267723	1,640246
Ret_silver_L1	-1,87474	0,325233	-5,76	0,000	-2,51219	-1,2373
Ret_sp500_L1	0,298761	0,081411	3,67	0,000	0,139199	0,458322
Ret_gold_L1	-3,49116	0,322847	-10,81	0,000	-4,12393	-2,85839
Pc_volume_usd_xpr_L1	0,018672	0,00653	2,86	0,004	0,005875	0,03147
Pc_volume_usd_xpr	0,0569	0,006838	8,32	0,000	0,043497	0,070304
cons	0,035511	0,010137	3,5	0,000	0,015644	0,055378
ARCH (L1)	6,208683	0,785265	7,91	0,000	4,669592	7,747774
const	0,036729	0,011093	3,31	0,001	0,014987	0,05847

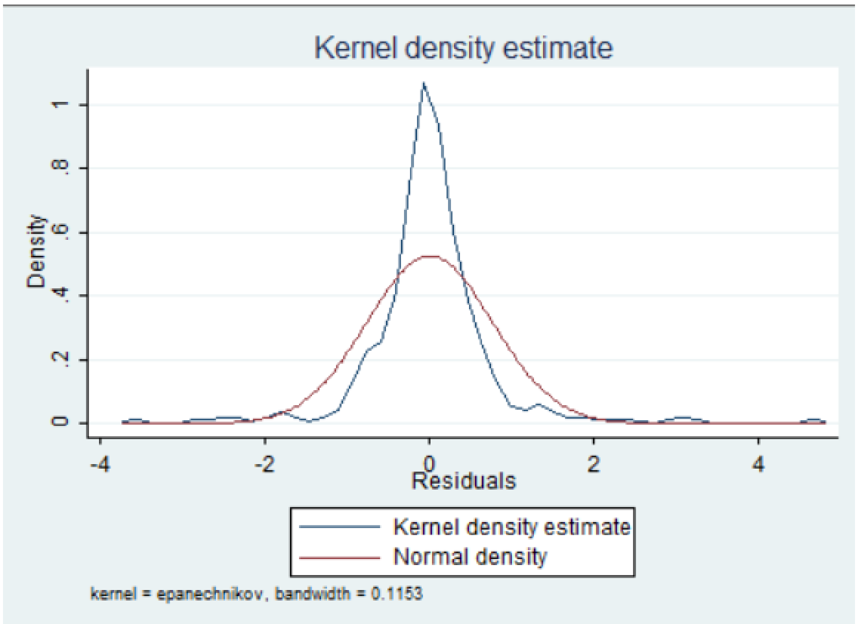

Figure 4. Kernel Density Estimation with Normal Density for the XPR model's residuals

Table 15. Normality Analysis of Residuals for the XRP

Skewness/Kurtosis test for normality					
Variable	Obs	Pr (Skewness)	Pr (Kurtosis)	adj chi2 (2)	Prob>chi2
e_norm	251	0,0000	0,0000	57,02	0,0000

Table 15 shows that the residuals of the regression are not characterized by a normal distribution, since the p-value is lower than 0.05. See also Figure 4.

Table 16. Results of the Analysis of Homoscedasticity of Random Components for the XRP

Breusch-Pagan	
F (6,243)	1,87
Prob>F	0,0864

Looking at the result of the Breusch-Pagan test, shown in Table 16, we can see that there are no grounds for rejecting the hypothesis of homoscedasticity of the random components.

Table 17. Results of the Ramsey Reset test for the XRP

Ramsey Reset	
F (3,240)	0,27
Prob>F	0,7422

In order to verify the assessment of the linearity of the regression function, the Ramsey Reset test was carried out. Looking at table 17, we can see that the results indicate that the specification of the model is correct (the p-value is equal to 0.7).

The conducted diagnosis of the regression model using the analysis of the normality of the residuals distribution, the homoscedasticity of the random components, and the Ramsey Reset test indicates (apart from the normality of the residuals distribution) that the model that we use for the XPR is correct.

6. Conclusions

In this work, we analyse the main determinants of cryptocurrencies returns. We have analysed the four most used cryptocurrencies – bitcoin, ethereum, litcoin, and ripple -, using data between 2013 and 2018 and estimating ARCH-type models. The models used in this dissertation, in comparison with other research work, include detailed internal cryptocurrency data, like generated coins and value of transactions. We have also used four cryptocurrencies, when previous work to ours, used the maximum of two.

The determinants pointed out by the recent literature on cryptocurrency markets are shown to be significant in our estimations. There are two determinants that have always the same sign in every estimation – the return of the USD (in the contemporaneous period), with a negative sign, and the cryptocurrency volume of transactions, with a positive sign. The returns of the USD, lagged one period, for Ripple, shows a positive sign. Regarding the returns of the euro (contemporaneous), for Bitcoin and Ripple, we have a positive relationship between these returns and the returns for each cryptocurrency. For the Ethereum the sign is negative. For the euro returns (in the previous period), we have a negative relationship with the Bitcoin, the Ethereum, and the Litecoin, but positive for the Ripple. The returns of silver (contemporaneous) show a negative relationship with the Bitcoin returns (using the ARCH-in-mean model), but positive for the Bitcoin (with TARCH), for the Ethereum, and the Ripple. The lagged returns of silver show a positive sign for the Bitcoin (both ARCH-in-mean and TARCH models), and for the Litecoin, but negative for the Ethereum and the Ripple. For the returns of gold (previous period) the sign of the coefficient is negative for the Bitcoin (both ARCH-in-mean and TARCH) and the Ripple, and positive for the Ethereum. Regarding the returns of the SP500 Index the relationship with the cryptocurrencies return is negative for the Bitcoin (ARCH-in-mean model), the Ethereum, and the Litecoin, and positive for the Bitcoin (TARCH model) and the Ripple. Finally, the number of generated coins in each cryptocurrency market has a negative relationship with the returns of each cryptocurrency, for the BTC and the Ethereum, but negative for the Litecoin.

Regarding further research, it would be interesting to assess how “traditional” investment assets are connected with cryptocurrencies and if cryptocurrencies can be taken into account in investment risk diversification.

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