Which factors can explain the returns of Bitcoin and other cryptocurrencies?

This paper aims to determine the factors that affect the returns of a majority of 44 of the largest cryptocurrencies, which already existed on October 30th, 2017. Prior studies used factors like trade volume, gold, oil, the stock market, and Google searches to explain the price movements of Bitcoin. To examine the effects of those factors on multiple cryptocurrencies, I used three different types of models (normal time series, Distributed-Lag and Vector-Autoregressive) in combination with daily and weekly data. To check whether Bitcoin was the dominant factor for the other cryptocurrencies, a variable with the Bitcoin returns was added to those models. The regressions show that trade volume and the S&P500 have a significant effect on the returns of Bitcoin and a majority of the altcoins, with Bitcoin having a significant effect on all altcoins as well. The Vector-Autoregressive model with weekly data proves to have the best goodness-of-fit for almost every cryptocurrency, indicating that the addition of a lagged variable of the returns of the cryptocurrencies increases the explainability of the model.

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1. Introduction

In the past few years, cryptocurrencies have become more and more popular and well-know to the public. They are financial assets with distinctive features that sets them apart from traditional assets. For example, their fundamental values are unclear, they are not backed by any government, there are no central clearing organizations to execute the payments and the supply is extremely difficult to manipulate due to the blockchain technology. These features make the evaluation of cryptocurrencies difficult and that is why I aim to contribute to the literature by trying to explain the factors that affect the returns of cryptocurrencies.

The beginning of the cryptocurrency market can be traced back to 2008, when Satoshi Nakamoto published the whitepaper of 'Bitcoin: A Peer-to-Peer Electronic Cash System'. The main idea of Nakamoto was to create a purely peer-to-peer version of electronic cash to allow online payments to be sent directly from one party to another without going through a financial institution (Nakamoto, 2008). Nakamoto started with the usual framework of coins made from digital signatures, but proposed a peer-to-peer network using proof-of-work to record a public history of transactions, making it computationally impractical for an attacker to change this history if the honest nodes control the majority of CPU power (Nakamoto, 2008).

On the 7th of January 2018, the market capitalization of all cryptocurrencies briefly exceeded $850 billion dollars, but two years later, less than $200 billion of that market capitalization, with Bitcoin's dominance at 65%, has remained (CoinGecko, 2020). In March 2020, more than 7,000 cryptocurrencies were created (CoinGecko, 2020), but it is unclear how many are still being used or worked on. Even more remarkable is the fact that out of the current top 100 cryptocurrencies, 63 are down more than 80% from their all-time highs. Table 1 below illustrates the volatility regarding five of the largest cryptocurrencies compared to the stock market and gold price between November 5th, 2017 and March 31st, 2020.

Table 1. Descriptive statistics of seven variables					
VARIABLES	**N**	**Mean**	**SD**	**Min**	**Max**
BTC	878	0.000814	0.0441	-0.372	0.252
ETH	878	0.000543	0.0529	-0.423	0.265
XRP	878	0.00203	0.0699	-0.329	0.835
LTC	878	0.00136	0.0605	-0.362	0.476
BCH	878	0.00159	0.0759	-0.430	0.540
SP500	878	.0000718	0.0119	-0.120	0.0940
GOLD	878	0.000289	0.00748	-0.0480	0.0760

Note: Descriptive statistics of seven variables: Total observations (N), average daily return (Mean), daily standard deviation (SD), lowest daily return (Min) and maximum daily return (Max)

As far as Bitcoin goes, its value rose from less than $1 to almost $20,000 in December 2017, dropped to $3,200 in December 2018 and is currently trading about 65% below its all-time high. All of these events happened recently and have therefore not been researched a lot. That is why the main idea of this paper is to create a model that can explain the performance of more than 40 of the largest and most active cryptocurrencies. The two current largest cryptocurrencies besides Bitcoin will be explained in the following paragraphs.

Bitcoin was mainly created to be a peer-to-peer version of electronic cash (Nakamoto, 2008), other cryptocurrencies, also called altcoins, were created with different purposes in mind. Altcoins is a combination of the words 'alternative Bitcoin' and this term is often used to describe all other cryptocurrencies besides Bitcoin.

The second largest cryptocurrency, based on market capitalization, is Ethereum and it was created by Vitalik Buterin in 2015 (Ethereum.org, 2020). Ethereum can best be described as a programmable blockchain, where developers can build their own decentralized applications on the Ethereum blockchain (Ethereum.org, 2020). Examples of these decentralized applications (dapps) are cryptocurrency wallets, financial applications, decentralized markets, and games. The currency used on the Ethereum blockchain is called ETH and serves two main purposes: ETH is used to pay for transactions on the blockchain and given to the miners as a reward for mining a block.

The third largest cryptocurrency at this moment is called XRP, which is the token used to transfer value across the Ripple Network (Cointelegraph, 2020). The main benefit of Ripple is the ability to confirm international transactions within 4 seconds on average with a cost of $0.00001 per transaction. However, unlike Bitcoin and Ethereum, Ripple does not have a blockchain, but Ripple has its own technology called the Ripple Protocol Consensus Algorithm (RPCA) (Cointelegraph, 2020). This RPCA can be seen as one of the largest downsides of Ripple, because the network is highly centralized and 61% of the XRP tokens are still owned by the company Ripple itself (Cointelegraph, 2020).

In order to be able to create a model that can explain the performance of cryptocurrencies, first the existing relevant literature will be reviewed to find potential influential factors, which serves as a basis for this research. Furthermore, the research problem will be defined after the literature review, followed by the methodological approach & research method.

2. Literature review

In traditional markets, multiple common risk factors affecting the returns on stocks and bonds exist. Since cryptocurrencies are special types of financial assets, we draw on the literature that tries to explain stock returns in order to gain insights on the factors that determine the value of cryptocurrencies. According to Fama and French (1993), there are three stock-market factors: an overall market factor, a factor related to the size of a firm and a factor related to the book-to-market equity. They also define two bond-market factors: one related to the maturity of the bond and the other one related to the default risk. Combined, these five factors seem to explain average returns on stocks and bonds (Fama & French, Common risk factors in the returns on stocks and bonds, 1993). However, the market for cryptocurrencies differs from traditional markets like the stock market and the factors mentioned by Fama and French (1993) might not be able explain the average returns of cryptocurrencies.

A few papers have done research into the factors which affect the price development of cryptocurrencies. Kjaerland et al. (2018) used the Autoregressive Distributed Lag (ARDL) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach to examine potential price drivers of Bitcoin. Their ARDL-model is estimated using ordinary least squares, including lags of both the dependent and independent variables. Their GARCH-model controls for homoscedasticity by testing the unconditional variance of the regression, meaning that the most recent observations have greater impacts on the predicted volatility.

One of outcomes of their research is that search results measured by Google Trends, has a positive impact on the price of Bitcoin. This is consistent with Kristoufek (2015), who also found evidence that Google searches boosted the price of Bitcoin. Another factor that has a positive impact on the price of Bitcoin, according to Kjaerland et al. (2018), is the S&P500. This result is also found in the paper of Dyhrberg (2016), who suggest that a positive shock in the stock market could make investors more risk seeking and willing to invest in alternative assets like Bitcoin. Interestingly, Ciaian et al. (2016) found that the Dow Jones tends to have a relatively small impact on the Bitcoin price in the short run and does not significantly affect the Bitcoin price in the long run. Thirdly, the oil price has a significant impact in the short run, but an insignificant impact on the price of Bitcoin in the long run according to Ciaian et al. (2016). The insignificant effect in the long run is supported by the findings of Kjaerland et al. (2018), but the significant impact of oil on the price of Bitcoin in the short run is contradicted by Bouri et al. (2018) due to their advanced ARDL models. Finally, Van Wijk (2013) shows that the oil price negatively influences the value of Bitcoin in the long run and argues that an increase in the oil price leads to a decrease in the budget of households, who consequently have less money to spend on other goods like Bitcoin. This decreases the demand for Bitcoin and ultimately decreases its value.

However, most of the research into the performance of cryptocurrencies is mainly focussed on Bitcoin. Madan et al. (2014) attempt to apply machine-learning algorithms to predict the Bitcoin price. They selected 16 independent features relating to Bitcoin trading and the Bitcoin network, including the market capitalization, miner's revenue, total Bitcoins, and trade volume to predict the future change in price of Bitcoin. Greaves & Au (2015) have done similar research as Madan et al. by investigating the predictive power of blockchain network-based features on the future price of Bitcoin. Their features include the current Bitcoin price, number of transactions per hour, total number of Bitcoin mined and the number of new addresses. A study by Ji et al. (2019), where they used different types of deep learning methods for Bitcoin price prediction is comparable to the previous two studies. Once again, they chose multiple Bitcoin blockchain features, including the cost per transaction, market capitalization, number of wallets created and the trade volume. The results from Madan et al. had a 50-55% accuracy in predicting the sign of future price change, when using 10-minute time intervals. This accuracy is comparable to that of Greaves & Au (2015), who report a 55% classification accuracy of up-down Bitcoin price movement. Finally, Ji et al. (2019) conclude that deep learning models seem to predict the Bitcoin price very well in terms of the regression analysis, but it is still too early to only use those kinds of models for algorithmic Bitcoin trading.

Two other studies, Liew et al. (2019) and Valencia et al. (2019), did research on the price movement prediction of not only Bitcoin, but altcoins as well. Liew et al. (2019) examined the largest 100 cryptocurrency returns from 2015 to early 2018 and found that predicting cryptocurrency movements with machine learning and artificial intelligence algorithms is only marginally attractive, with variation in the predictability power per cryptocurrency. Interesting findings were that lower volatile cryptocurrencies are more predictable than volatile ones and short-term predictability is very weak, indicating a semi-strong form of efficiency for near-term cryptocurrency markets (Liew, Li, Budavari, & Sharma, 2019). Valencia et al. (2019) show that there is at least one model that can predict market movements of Bitcoin, Ethereum, Ripple and Litecoin based on their precision scores. These predictions are limited to the direction of the market and cannot predict the duration or magnitude of the market movement. Furthermore, the results among the four cryptocurrencies were quite different, with the best results for Bitcoin and the lowest accuracy for Ethereum (Valencia, Gomez-Espinosa, & Valdes-Aguirre, 2019).

2.1 Hypotheses

Ammous (2018) states that gold holds a monetary role in the world economy today, despite not being any nation's official currency, as it is used as a reserve asset by central banks and as a store of value by many individuals all over the world. The reason that gold is able to maintain this role is due to two unique characteristics, which differentiate gold from other commodities: gold is virtually impossible to destroy and can only be extracted from its unrefined ore (Ammous, 2018). The yearly growth rate of the gold supply has been around 1.7% for the past seven decades, never exceeding 2%, which shows a strong predictability of the supply. This makes gold an attractive store of value compared to a traditional currencies like the dollar with an average annual increase in broad money supply of respectively 5.4% between 1990 and 2015 (Ammous, 2018). With Bitcoin, the supply growth is already determined in its entirety, with a halving of the growth rate every 4 years and a fixed circulating supply of 21 million Bitcoins around the year 2140 (Ammous, 2018). Gold is also used as a safe asset by investors in risky times and cryptocurrencies can have a similar function. The predictability of the future supply and the potential of a safe asset are arguments that investors are starting to look at Bitcoin (and other cryptocurrencies with a similar characteristics as Bitcoin) in the same way they currently view gold, which is why the returns on gold are expected to have a positive effect on the returns of cryptocurrencies.

Kjaerland et al. (2018) agree with Ammous (2018) that gold is considered to be an important global commodity with impact on all almost all economies around the world. The ARDL-models of Kjaerland et al. (2018) show a positive, but insignificant, relationship between the price of gold and Bitcoin between the first week of 2013 until the seventh week of 2018. Jareño et al. (2020) also found a positive (and statistically significant) relationship in the long- and short-run between Bitcoin and gold price returns with their non-linear ARDL approach. A third study that presented a significant relation between Bitcoin and gold was that of Bouri et al. (2018), where they concluded that commodities, including gold, are significant factors driving the Bitcoin prices. The first hypothesis is:

H1: The returns on gold have a positive effect on the price returns of the cryptocurrencies.

Another important global commodity with a worldwide impact, besides gold, is oil. The ARDL-models of Kjaerland et al. (2018) show a negative relationship between Bitcoin and oil, which is the opposite of the relationship they found between Bitcoin and gold. The same negative relationship is noted by Jareño et al. (2020) at low quantiles in their regression, but unlike the results of Kjaerland et al. (2018), these results are statistically significant at the low quantiles in their regression. This indicates that an increase in the oil price, would decrease the price of Bitcoin in a recession. According to Van Wijk (2013), the negative relationship between Bitcoin and oil makes sense. A decrease in the budget of

consumers due to higher expenditures as a result of a higher oil price, leads to less demand for Bitcoin and a lower price. These findings have led to the second hypothesis:

H2: The oil price returns have a negative effect on the price returns of the cryptocurrencies.

A factor used in multiple studies trying to explain the price movement of Bitcoin is the S&P500. Liew et al. (2019) shows a positive correlation between Bitcoin and the S&P500 in the period of January 2015 until February 2018. Moreover, Kjaerland et al. (2018) show in their ARDL- and GARCH-models that the relationship between Bitcoin and the S&P500 is positive and significant, meaning that the price of Bitcoin increases when the S&P500 increases. Furthermore, this independent variable had the largest coefficient in their regression, which makes it the most influential factor on the Bitcoin price.

Thirdly, Dyhrberg (2016) suggest that a positive shock in the stock market could make investors more risk seeking and willing to invest in alternative assets like Bitcoin, supporting the positive relationship between Bitcoin and the S&P500 made by the other researchers. The third hypothesis therefore states:

H3: The SP500 has a positive effect on the price returns of the cryptocurrencies.

Looking at past research on the effects of trade volume on the returns of cryptocurrencies, Aalborg et al. (2018) found a small positive effect in their descriptive model for Bitcoin returns on weekly data. Results based on the p-values of a CGCQ test from Bouri et al. (2019), trade volume strongly Granger-causes price returns of all seven cryptocurrencies in both high (superior performance) and low (poor performance) quantiles. Balcilar et al. (2017) argue that their causality-in-quantiles test reveal that volume can predict the returns of Bitcoin, except for Bitcoin bear and bull market regimes. This indicates that volume can predict returns when the volume is around the median, providing investors with valuable predictive information. These findings, combined with the price explosion of the cryptocurrencies at the end of 2017 and beginning of 2018, have led to the fourth hypothesis:

H4: Trade volume has a positive effect on the price returns of the cryptocurrencies.

The research of Liew et al. (2019) shows an overwhelming positive correlation between Bitcoin and altcoins based on daily returns, with 98 out of 99 altcoins having a positive correlation with Bitcoin between January 2015 and February 2018. Correlations based on weekly returns indicate the same results but show more negative correlations between certain altcoins and Bitcoin than the daily returns. Liew et al. (2019) is not the only researcher that found overwhelming evidence of correlation between Bitcoin and altcoins. Gandal and Halaburda (2016) found a correlation of 0.93 between Bitcoin and Litecoin between October 2013 and April 2014, while the correlation before that period was small and negative. The other cryptocurrencies in their sample (Peercoin, Namecoin, Feathercoin, Novacoin, and

Terracoin) also show a positive and large correlation (above 0.7) between October 2013 and April 2014. These findings, together with the fact that Bitcoin has always been the cryptocurrency with the highest market dominance (currently at 65% according to CoinGecko (2020)), has led to the following hypothesis:

H5: The Bitcoin price has a positive effect on the price returns of the altcoins.

Early research from Kristoufek (2015) into the relationship between the price of Bitcoin and Google searches shows a positive correlation in the long run between September 2011 and April 2014. Interestingly, Kristoufek (2015) notes a shift in the relationship in that period, where the relationship is led by prices in the first third, while the search query leads the prices in the final third. More recent research of Kjaerland et al. (2018) confirms the positive relationship between Google and Bitcoin in their ARDL- and GARCH-models. According to their findings, when people's curiosity and interest in Bitcoin (measured by the Google Trends Score) increases, the demand and therefore the price of Bitcoin increases as well. These findings lead to the final hypothesis:

H6: The Google Trends score has a positive effect on the returns of the cryptocurrencies.

3. Research problem

This paper tries to determine the factors that affect the returns of many cryptocurrencies, instead of trying to explain the future price of Bitcoin or the other few large altcoins like Ethereum and Ripple. In the literature review, it became clear that the researchers mostly concentrated their attention on estimating the future price of Bitcoin by looking at the specific blockchain features. Some research was done on factors that could influence the price of cryptocurrencies, like Google searches, returns of the stock market or the gold/oil price. The problem with those papers is that the research was either conducted in the early years of the cryptocurrency market (before the price surge at the end of 2017) or solely focussed on Bitcoin.

The gap in the literature exists because there is barely any information about the factors that could possibly explain the returns of altcoins, before and after the price surge in December 2017 and January 2018. As mentioned in the introduction, the total amount of cryptocurrencies exceeds 7,000 (CoinGecko, 2020) and the factors that explain their returns are currently unknown. Because of the reasons above, this paper answers the following research question:

Which model can explain the returns of cryptocurrencies the best?

4. Methodological approach and research method

Using a quantitative approach is the best way to answer the research question, which is stated in the previous chapter. The analysis of multiple variables and their effect on the performance of cryptocurrencies can best be researched with existing data. Multiple websites record data of cryptocurrencies and three of them are extremely useful for this paper: Yahoo Finance[1] (daily and weekly data on the price of cryptocurrencies), Coingecko[2] (overall useful information) and CoinMarketCap[3] (overview of historical data of all cryptocurrencies and their past market capitalization).

The daily data ranges from November 4th, 2017 until March 31st, 2020, while the weekly data consists of the period between October 30th, 2017 until March 30th, 2020. This period includes the price surge of late 2017 and early 2018, followed by a price correction in the months after that and the crash of March 2020 because of the coronavirus. In total, 44 of the largest cryptocurrencies, which already existed on October 30th, 2017, will be researched. A complete list of these cryptocurrencies can be found in the appendix.

Since the data entails multiple moments in time, Prais-Winsten regressions will be run to find the best model. The advantage of the Prais-Winsten regression is that this type of regression removes the autocorrelation in the data and adjusts the t-statistic accordingly. The original Durbin-Watson statistic will show if there is autocorrelation in the original data and the transformed Durbin-Watson statistic is going to show if the Prais-Winsten regression has successfully adjusted the t-statistic by removing the autocorrelation from the regression. The three different types of models that will be tested are the Prais-Winsten regression without lagged variables, the Distributed Lags model, and the Vector-Autoregressive model. The models for the altcoins are slightly different from the Bitcoin-models, because of the addition of the BTC-variable.

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[1] https://finance.yahoo.com/cryptocurrencies
[2] www.coingecko.com
[3] www.coinmarketcap.com

4.1 Variables

The dependent variable in all of the models is either the daily or weekly return of the cryptocurrency itself and is written as 'R_t' in the models. As mentioned in chapter 3.1, the following variables are used to determine their impact on the performance of the cryptocurrencies:

- *Change in daily and weekly trade volume (Volume)*

The change in daily and weekly trade volume (measured in USD) shows the interest in the particular cryptocurrency. The data is retrieved from Yahoo Finance (2020) in collaboration with CoinMarketCap. This variable will show if the current and past trade volume have a significant impact on the price of cryptocurrencies. The combination of the past and current trade volume in some of the regressions can show the effects at the same time, while keeping the amount of models to a minimum.

- *Daily and weekly returns of gold (Gold)*

The data of the daily and weekly returns of gold is also downloaded from Yahoo Finance (2020). The relevance mainly lies in the similarities between the characteristics of gold and Bitcoin, like the predictability of the future supply and the potential of Bitcoin to serve as a store of value comparable to gold (Ammous, 2018). This variable will show if the returns of cryptocurrencies followed the current or lagged returns of gold in the past.

- *Daily and weekly returns of oil (Oil)*

This variable measures the effects of the change in the price of oil on the prices of the cryptocurrencies and it is used in the daily and weekly models together with one lag of oil price returns.

- *Daily and weekly returns of the S&P500 (SP500)*

The daily and weekly change in price of the S&P500 index (500 largest American companies based on market capitalization) is used as a variable in multiple models, including lagged variables of the S&P500 to measure the effect of price changes in this index on the prices of cryptocurrencies.

- *Daily and weekly change Bitcoin price (BTC)*

The Bitcoin price returns will be included in the models of the 43 cryptocurrencies besides Bitcoin, because of the dominance of Bitcoin on the total cryptocurrency market. To illustrate this: on April 1st, 2020, the market capitalization of Bitcoin made up about 65% of the total market.

- *Change in weekly Google Trends score (Google)*

Google Trends score for searches is only recorded on a weekly basis for a period of 2,5 years and the change in the score is therefore only included in the weekly models. The search term of each cryptocurrency includes the word 'crypto', to make sure that people specifically searched the searches were specifically meant for the currencies, and looks like this: "Bitcoin crypto", "Ethereum crypto". The maximum score is 100 and indicates the highest interest in the search term in that specific week. Accordingly, a score of 50 means that the search interest was half the size of the week where the score was 100.

- *Lagged daily and weekly returns of the cryptocurrencies itself (Lag)*

For the Vector-Autoregressive models, one lag of the dependent variable (the returns of the cryptocurrency) is included. The main advantage of this lag is that the independent variables in the model only have to explain the difference between the current price and the price of one day/week ago, instead of the current price.

4.2 The models

In total, six models will be compared for each cryptocurrency to test their ability to explain the returns of those cryptocurrencies. Models 1-3-5 use daily data, while models 2-4-6 use weekly data and have an additional variable named 'Google'. The models for Bitcoin differ slightly from the models for the altcoins, which have an additional variable called 'BTC' (bold in the formulas below).

The first and second model are time series regressions with the following variables:

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Gold_t - \beta_3 Oil_t + \beta_4 SP500_t + \boldsymbol{\beta_5 BTC_t} + e_t \quad (1)$$

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Gold_t - \beta_3 Oil_t + \beta_4 SP500_t + \boldsymbol{\beta_5 BTC_t} + \beta_6 Google_t + e_t$$
$$(2)$$

The third and fourth model are distributed lags models with all the following variables:

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Volume_{t-1} + \beta_3 Gold_t + \beta_4 Gold_{t-1} - \beta_5 Oil_t - \beta_6 Oil_{t-1} +$$
$$\beta_7 SP500_t + \beta_8 SP500_{t-1} + \boldsymbol{\beta_9 BTC_t} + \boldsymbol{\beta_{10} BTC_{t-1}} + e_t \quad (3)$$

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Volume_{t-1} + \beta_3 Gold_t + \beta_4 Gold_{t-1} - \beta_5 Oil_t - \beta_6 Oil_{t-1} +$$
$$\beta_7 SP500_t + \beta_8 SP500_{t-1} + \boldsymbol{\beta_9 BTC_t} + \boldsymbol{\beta_{10} BTC_{t-1}} + \beta_{11} Google_t + \beta_{12} Google_{t-1} + e_t$$
$$(4)$$

The fifth and sixth model are Vector-Autoregressive models the following variables:

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Volume_{t-1} + \beta_3 Gold_t + \beta_4 Gold_{t-1} - \beta_5 Oil_t - \beta_6 Oil_{t-1}$$
$$+ \beta_7 SP500_t + \beta_8 SP500_{t-1} + \boldsymbol{\beta_9 BTC_t} + \boldsymbol{\beta_{10} BTC_{t-1}} + \beta_{13} R_{t-1} + e_t$$
$$(5)$$

$$R_t = \beta_0 + \beta_1 Volume_t + \beta_2 Volume_{t-1} + \beta_3 Gold_t + \beta_4 Gold_{t-1} - \beta_5 Oil_t - \beta_6 Oil_{t-1}$$
$$+ \beta_7 SP500_t + \beta_8 SP500_{t-1} + \boldsymbol{\beta_9 BTC_t} + \boldsymbol{\beta_{10} BTC_{t-1}} + \beta_{11} Google_t$$
$$+ \beta_{12} Google_{t-1} + \beta_{13} R_{t-1} + e_t$$
$$(6)$$

5. Results

This chapter includes the results of the Prais-Winsten regressions of the models explained in paragraph 4.2 and 4.3. The full results of the 5 largest cryptocurrencies are shown in the following paragraphs, with an overview of the most important results of the other 39 cryptocurrencies in the final part of the results.

Before the results of the individual cryptocurrencies are discussed, table 2 below shows the amount of times for each of the six models that there was no evidence of autocorrelation in the original and transformed regression. The original Durbin-Watson statistic shows that only in model 2 and 4 (both weekly models), 12 and 13 cryptocurrencies show signs of autocorrelation, while the other models indicate almost no evidence of autocorrelation. Nevertheless, using Prais-Winsten instead of OLS improves the amount of times the regressions show no evidence of autocorrelation and is therefore a better way to test the variables for their impact on the price returns of cryptocurrencies.

Table 2. Test for autocorrelation

Model	Original Durbin-Watson	Transformed Durbin-Watson
#1	43	44
#2	32	43
#3	40	44
#4	31	44
#5	44	44
#6	41	44

Note: The numbers in the table show the amount of times there was **no** evidence of autocorrelation out of a total of 44 regressions per model.

5.1 Bitcoin results

Table 3 shows the results of the regressions of the 6 models for Bitcoin mentioned in paragraph 4.2. The volume in the current period is positive and significant on a 1%-level in five of those models, with only the second model showing no significance. Trade volume in the previous period is also positive and significant on a 1%-level for models 4 and 6 as well, shows a significant positive impact on a 10%-level in the fifth model and no significance in the third model. The positive coefficient indicates that an increase in the trade volume in the current or previous period, leads to higher Bitcoin returns in the current or next period.

The current gold price returns do not have a significant impact on the returns of Bitcoin in any of the six models. The gold price returns of the previous day, however, show a positive and significant impact on the returns of Bitcoin on a 5%-level in the fifth model. This means that a 1% return on gold yesterday, will lead to a 0.386% return on Bitcoin today.

Oil price returns show no significance on the Bitcoin returns in each of the six models. The lag of the oil price returns has a negative effect on the returns on Bitcoin, with significance on a 1%-level in models 3 and 5. This shows that rising oil prices lead to negative returns for Bitcoin the following day.

The variable for the returns of the S&P500 shows a positive relationship between the current returns of the S&P500 and the returns on Bitcoin, with a significance level of 1% for the daily models. Meaning that an increase in the price of the S&P500 today, would also lead to an increase in the price of Bitcoin on the same day.

In the fifth and sixth model, a lag of the dependent variable was added to check whether the previous return has a significant impact on the returns in the current period. In the daily model, the variable is negative and significant on a 1%-level, indicating that a positive return on the previous day, would lead to a negative return on the following day. The lag of Bitcoin returns in the weekly model is positive but shows no signs of a significant impact on the current returns on Bitcoin.

The last variable is the change in the Google Trends Score, which shows small coefficients and no significant impact on the returns of Bitcoin in any of the models.

Finally, the adjusted R-squared is the highest for model 6. This means that the variables in that model fit the regression line the best, but the score of 0.2867 shows that the goodness-of-fit is quite low.

Table 3. Bitcoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Volume$_t$	0.0363***	-0.00779	0.0368***	0.262***	0.0352***	0.273***
	(0.00719)	(0.0213)	(0.00723)	(0.0617)	(0.00714)	(0.0626)
Volume$_{t-1}$			0.00806	0.0704***	0.0135*	0.0738***
			(0.00720)	(0.0192)	(0.00720)	(0.0192)
Gold$_t$	0.221	0.688	0.277	0.575	0.306	0.564
	(0.195)	(0.565)	(0.194)	(0.564)	(0.195)	(0.564)
Gold$_{t-1}$			0.317	-0.541	0.386**	-0.421
			(0.196)	(0.531)	(0.195)	(0.529)
Oil$_t$	0.0319	0.124	-0.0544	0.0971	-0.0531	0.139
	(0.0546)	(0.233)	(0.0587)	(0.252)	(0.0581)	(0.254)
Oil$_{t-1}$			-0.246***	-0.118	-0.241***	-0.155
			(0.0599)	(0.213)	(0.0591)	(0.215)
SP500$_t$	0.679***	0.359	0.793***	0.573	0.779***	0.531
	(0.123)	(0.475)	(0.129)	(0.435)	(0.128)	(0.439)
SP500$_{t-1}$			0.0352	0.370	0.143	0.166
			(0.126)	(0.499)	(0.127)	(0.503)
BTC$_{t-1}$					-0.205***	0.118
					(0.0329)	(0.0906)
GOOGLE$_t$		0.0940		-0.0848		-0.0924
		(0.0596)		(0.0681)		(0.0696)
GOOGLE$_{t-1}$				-0.000753		-0.0211
				(0.0552)		(0.0554)
Constant	-.0000341	0.00515	-0.000599	-0.00557	-0.000555	-0.00694
	(0.00143)	(0.0108)	(0.00144)	(0.00941)	(0.00180)	(0.00850)
Observations	878	126	877	125	877	125
Adj. R-squared	0.0548	0.0138	0.0714	0.2370	0.1143	0.2867
DW (original)	2.038684	2.026567	2.021806	2.058484	1.988385	1.989942
DW (transformed)	1.998297	1.975347	1.995941	1.917608	1.993464	1.932051

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Ethereum, Ripple, Bitcoin Cash and Litecoin results

In this paragraph, the results of the regressions of Ethereum, Ripple, Bitcoin Cash, and Litecoin are shown and discussed in detail here. The detailed information can be found in tables 4-7. Starting with the current trade volume of the four largest cryptocurrencies after Bitcoin, all six models of each of the altcoins show a positive and significant effect on a 1%-level. The coefficient is larger in the weekly models compared to the daily models, indicating that an increase in the weekly volume has a greater impact on the returns than the daily volume. The results of the lagged variable for trade volume are more dispersed, with positive significant effects for Ethereum and Ripple in models 3-5; Bitcoin Cash showing positive and significant effects in models 3, 5, 6; and lastly, Litecoin displaying a positive and significant impact of the lagged trade volume in the 3rd, 4th and 6th model. Given the amount of significance in almost every model, the past trade volume is an important factor affecting the returns of the cryptocurrencies. These results are in line with the Bitcoin results from the previous paragraph, indicating that the trade volume has a considerable impact on the returns of Bitcoin and the four largest altcoins.

All models of the four altcoins show no significant influence of the current and past gold price returns on the returns of the altcoins. These results are in contrast with the finding of a significant positive effect for the gold returns of the previous day in the fifth model of Bitcoin. A reason for this result might be that investors believe that only one cryptocurrency can be compared to gold, which is Bitcoin.

The current oil price returns in the Ethereum regressions present three positive significant effects for the daily models (1/3/5), which are also the only notable significant effects for the oil price returns of the four altcoins. Interestingly, the current oil price having a positive effect on the price of Ethereum is the opposite of the findings in the Bitcoin regressions where the oil price returns had a significant negative impact on the returns.

Comparable to the results of the Bitcoin models, the current returns of the S&P500 have a positive and significant effect on Ethereum, Ripple, and Litecoin. In the Ethereum regressions, the effects can be seen in all three daily models, while Ripple shows a significant impact on a 10%-level in the first and third model. The impact of the S&P500 on Litecoin are noted in all six models, except the fourth one, meaning that the weekly returns of Litecoin will increase if the weekly returns of the S&P500 increase.

The positive impact of the current Bitcoin returns on the other four altcoins returns is found in every single model. The significance level is at 1% for all models, except for second one of Ethereum where it is 10%. This means that these altcoins will have positive returns when Bitcoin has positive returns that day. The lagged variable of Bitcoin provides different results for each altcoin. The Ethereum returns

are negatively affected by a price increase of Bitcoin in the previous period, with a significant negative impact in models 3, 5, and 6. Similar results can be found in the table with the regressions for Ripple, with a significant negative effect in models 3-6. Bitcoin Cash is showing contradicting results, with a significant negative effect in the two daily models, but a significant positive effect in both weekly models. Finally, the daily returns of Litecoin are negatively and significantly impacted by positive returns of Bitcoin on the previous day, and the weekly returns are negatively but insignificantly affected by positive Bitcoin returns in the previous week.

The past returns of Ethereum have a positive influence on the current returns of Ethereum, with an insignificant effect on the daily returns, but a 1% significant return on the weekly returns. The coefficient of the weekly returns indicates that a return in the previous week of 1%, will lead to a 0.3% return in the current week. For Ripple, positive effects can be seen in both models as well, but the significance level of 1% is present in model five and six. Once again, Bitcoin Cash is presenting contradicting results, with a positive and significant effect of the previous daily return and a negative and significant effect of the past weekly return. This means that a positive return yesterday will lead to a positive return today, but a positive return last week will lead to a negative return this week. Lastly, previous Litecoin returns have a positive impact on the current returns, with only the daily model showing significance.

A change in the Google Trends Score in the current week has a negative and significant effect on a 1%-level on the three weekly models of Ethereum. This indicates that the returns are already decreasing, while the interest of people in Ethereum, measured with the Google Trends Score, is still increasing. A change in the Google Trends Score of the previous week has no significant effect on the returns of Ethereum. The effect of the Google Trends Score on the returns of Ripple is negligible according to the small, negative, and insignificant coefficients. Similar results are found in the models of Bitcoin Cash and Litecoin, where the coefficients are small and insignificant.

Where the best model in the Bitcoin regressions only noted an adjusted R-squared of 0.2867, the four altcoins show a much better goodness-of-fit due to the added variable of Bitcoin returns. Ethereum, Ripple, Bitcoin Cash and Litecoin all have an adjusted R-squared of 0.73 or higher in the sixth model. The other weekly and daily models are also better able to explain the returns of the particular cryptocurrency than those of Bitcoin when comparing the adjusted R-squared between them.

Table 4. Ethereum regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0200***	0.269***	0.0229***	0.289***	0.0231***	0.302***
	(0.00493)	(0.0371)	(0.00506)	(0.0412)	(0.00509)	(0.0407)
$VOLUME_{t-1}$			0.0131***	0.0999**	0.0125**	0.00931
			(0.00505)	(0.0387)	(0.00513)	(0.0482)
$GOLD_t$	-0.0527	0.582	-0.0318	0.764	-0.0347	0.651
	(0.154)	(0.426)	(0.156)	(0.477)	(0.156)	(0.472)
$GOLD_{t-1}$			-0.0145	0.648	-0.0175	0.445
			(0.157)	(0.454)	(0.157)	(0.442)
OIL_t	0.0798*	0.0263	0.0932**	0.106	0.0937**	0.184
	(0.0409)	(0.178)	(0.0467)	(0.212)	(0.0468)	(0.209)
OIL_{t-1}			0.0223	-0.225	0.0200	-0.254
			(0.0480)	(0.180)	(0.0482)	(0.176)
$SP500_t$	0.352***	0.408	0.349***	0.251	0.350***	0.287
	(0.0962)	(0.364)	(0.105)	(0.378)	(0.105)	(0.364)
$SP500_{t-1}$			0.0682	-0.00509	0.0580	-0.324
			(0.102)	(0.416)	(0.103)	(0.413)
BTC_t	0.895***	0.824*	0.884***	0.829***	0.884***	0.819***
	(0.0264)	(0.0701)	(0.0269)	(0.0717)	(0.0270)	(0.0711)
BTC_{t-1}			-0.0798***	-0.0403	-0.113***	-0.277***
			(0.0267)	(0.0796)	(0.0400)	(0.103)
ETH_{t-1}					0.0382	0.303***
					(0.0340)	(0.0910)
$GOOGLE_t$		-0.0897***		-0.104***		-0.111***
		(0.0271)		(0.0289)		(0.0286)
$GOOGLE_{t-1}$				-0.0172		0.0121
				(0.0286)		(0.0297)
Constant	-0.000642	-0.00950	-0.000932	-0.0165**	-0.000915	-0.0123*
	(0.00135)	(0.00835)	(0.00136)	(0.00827)	(0.00131)	(0.00662)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5964	0.6635	0.6008	0.6782	0.5959	0.7361
DW (original)	1.727650	2.019722	1.718649	2.070047	1.971236	1.988673
DW (transformed)	1.985281	1.971833	1.980613	1.920207	1.985760	1.991830

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Ripple regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0373***	0.217***	0.0401***	0.247***	0.0401***	0.248***
	(0.00309)	(0.0163)	(0.00311)	(0.0176)	(0.00307)	(0.0170)
$VOLUME_{t-1}$			0.0129***	0.0677***	0.00736**	-0.00404
			(0.00311)	(0.0179)	(0.00334)	(0.0257)
$GOLD_t$	0.114	0.113	0.148	0.815	0.129	0.501
	(0.254)	(0.597)	(0.255)	(0.721)	(0.252)	(0.702)
$GOLD_{t-1}$			0.302	1.165	0.223	0.764
			(0.257)	(0.717)	(0.255)	(0.668)
OIL_t	0.0157	-0.0369	0.0236	-0.0232	0.0136	-0.0540
	(0.0681)	(0.279)	(0.0766)	(0.322)	(0.0762)	(0.314)
OIL_{t-1}			0.0152	-0.0619	-0.00683	-0.135
			(0.0788)	(0.272)	(0.0787)	(0.260)
$SP500_t$	0.312*	0.250	0.283*	0.147	0.279	0.211
	(0.159)	(0.514)	(0.171)	(0.563)	(0.172)	(0.539)
$SP500_{t-1}$			0.145	-0.0210	0.0920	-0.116
			(0.166)	(0.610)	(0.165)	(0.602)
BTC_t	0.729***	0.627***	0.717***	0.657***	0.709***	0.656***
	(0.0436)	(0.106)	(0.0440)	(0.112)	(0.0435)	(0.105)
BTC_{t-1}			-0.144***	-0.241**	-0.355***	-0.461***
			(0.0437)	(0.120)	(0.0480)	(0.118)
XRP_{t-1}					0.313***	0.399***
					(0.0313)	(0.0762)
$GOOGLE_t$		-0.0412		-0.0504		-0.00510
		(0.0251)		(0.0315)		(0.0310)
$GOOGLE_{t-1}$				-0.0230		-0.00521
				(0.0319)		(0.0314)
Constant	-0.00195	-0.0101	-0.00334	-0.0269*	-0.00330**	-0.0233**
	(0.00215)	(0.0195)	(0.00207)	(0.0160)	(0.00154)	(0.0109)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3553	0.7060	0.3683	0.7260	0.4315	0.7929
DW (original)	1.789888	1.446101	1.871768	1.710359	2.081517	2.170211
DW (transformed)	2.001917	1.917005	1.999984	1.917208	2.032603	1.981517

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Bitcoin Cash regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0681***	0.178***	0.0725***	0.161***	0.0726***	0.157***
	(0.00387)	(0.0151)	(0.00381)	(0.0126)	(0.00382)	(0.0124)
$VOLUME_{t-1}$			0.0262***	-0.00802	0.0185***	0.0452**
			(0.00381)	(0.0124)	(0.00450)	(0.0179)
$GOLD_t$	0.0789	0.142	0.0519	-0.205	0.0437	0.0405
	(0.234)	(0.713)	(0.231)	(0.639)	(0.230)	(0.627)
$GOLD_{t-1}$			0.120	0.153	0.110	0.266
			(0.233)	(0.595)	(0.233)	(0.611)
OIL_t	0.0531	0.322	0.0755	0.267	0.0714	0.136
	(0.0627)	(0.272)	(0.0693)	(0.280)	(0.0695)	(0.270)
OIL_{t-1}			0.0715	-0.167	0.0542	-0.0172
			(0.0713)	(0.237)	(0.0716)	(0.231)
$SP500_t$	0.130	0.275	0.119	-0.0143	0.120	0.0282
	(0.147)	(0.590)	(0.155)	(0.499)	(0.156)	(0.484)
$SP500_{t-1}$			0.178	-0.184	0.168	0.0572
			(0.150)	(0.554)	(0.150)	(0.520)
BTC_t	0.980***	0.701***	0.971***	0.755***	0.973***	0.834***
	(0.0401)	(0.110)	(0.0398)	(0.0936)	(0.0398)	(0.0940)
BTC_{t-1}			-0.131***	0.218**	-0.248***	0.376***
			(0.0394)	(0.0972)	(0.0503)	(0.103)
BCH_{t-1}					0.126***	-.307***
					(0.0328)	(0.0707)
$GOOGLE_t$		0.0236		0.0168		0.0200
		(0.0178)		(0.0145)		(0.0146)
$GOOGLE_{t-1}$				0.0206		0.0165
				(0.0147)		(0.0144)
Constant	-0.00325	-0.0182	-0.00498***	-0.0260**	-0.00464***	-0.0309**
	(0.00198)	(0.0115)	(0.00190)	(0.0104)	(0.00169)	(0.0140)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5366	0.6559	0.5611	0.7273	0.5648	0.7400
DW (original)	1.800619	2.078185	1.833061	2.258907	2.013704	1.864081
DW (transformed)	1.986171	1.590931	1.983572	1.957882	2.006371	1.939821

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Litecoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0516***	0.257***	0.0544***	0.280***	0.0550***	0.280***
	(0.00423)	(0.0290)	(0.00432)	(0.0322)	(0.00434)	(0.0322)
VOLUME$_{t-1}$			0.0117***	0.0979***	0.00661	0.0804**
			(0.00432)	(0.0284)	(0.00470)	(0.0387)
GOLD$_t$	-0.0400	0.0396	-0.0780	0.403	-0.0837	0.362
	(0.178)	(0.412)	(0.181)	(0.446)	(0.180)	(0.453)
GOLD$_{t-1}$			-0.259	0.357	-0.275	0.337
			(0.182)	(0.427)	(0.182)	(0.426)
OIL$_t$	0.0307	-0.223	0.0473	-0.185	0.0462	-0.182
	(0.0475)	(0.168)	(0.0542)	(0.195)	(0.0545)	(0.198)
OIL$_{t-1}$			0.0395	-0.249	0.0332	-0.233
			(0.0557)	(0.168)	(0.0561)	(0.171)
SP500$_t$	0.306***	0.766**	0.300**	0.573	0.307**	0.590*
	(0.111)	(0.347)	(0.121)	(0.349)	(0.122)	(0.353)
SP500$_{t-1}$			0.0295	0.360	0.00749	0.278
			(0.118)	(0.381)	(0.118)	(0.389)
BTC$_t$	0.921***	0.848***	0.915***	0.795***	0.916***	0.795***
	(0.0306)	(0.0702)	(0.0312)	(0.0708)	(0.0313)	(0.0717)
BTC$_{t-1}$			-0.0522*	-0.0612	-0.169***	-0.118
			(0.0310)	(0.0753)	(0.0434)	(0.107)
LTC$_{t-1}$					0.128***	0.0691
					(0.0336)	(0.0919)
GOOGLE$_t$		-0.00389		-0.0124		-0.0121
		(0.0173)		(0.0174)		(0.0175)
GOOGLE$_{t-1}$				-0.00475		-0.00401
				(0.0172)		(0.00172)
Constant	-0.00125	-0.0117	-0.00158	-0.0195**	-0.00150	-0.0186**
	(0.00155)	(0.00784)	(0.00154)	(0.00748)	(0.00136)	(0.00726)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5794	0.7603	0.5817	0.7904	0.5772	0.7971
DW (original)	1.737442	2.082460	1.758134	2.215913	1.997486	2.097392
DW (transformed)	1.977003	2.001546	1.975903	1.996472	1.998343	2.015570

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Results other 39 cryptocurrencies

In this subchapter, the most important findings from the 39 smaller altcoins will be shared. The details of these findings can be found in the tables in the appendices.

As seen in the models of the five largest cryptocurrencies, the current trade volume is one of the most important variables tested. The results from the smaller altcoins are in line with the results of the five largest cryptocurrencies and show a positive and significant effect in the daily and weekly models, except for the daily models of MaidSafeCoin and Factom. Results from the effect of past trade volume on the returns of the altcoins are more dispersed, showing no clear pattern across the various cryptocurrencies.

Most altcoins show the same insignificant effect of the current and past gold price returns that the four largest altcoins showed. However, positive, and significant effects were noted for three altcoins (Neo, OmiseGo and MaidSafeCoin) when looking at the current weekly gold price returns, while the current daily gold price returns have a positive and significant effect on the returns of Monero, Ark and Maid. Dash is the only altcoin in the sample where the past daily gold price has a negative and significant impact on the returns. The weekly past gold price returns show positive and significant effects on the returns of certain altcoins (Iota, Ethereum Classic, HyperCash and Bytecoin) and negative and significant effects on other cryptocurrencies (Zcash and Golem). The difference in the effect of the gold price returns on the various altcoins is a characteristic of the diversity between those cryptocurrencies.

The oil price returns turned out to be unable to explain the returns of the altcoins in almost every model. Negative and significant effects were found for Dash when looking at the current weekly oil price returns, while three other altcoins (Waves, TRX and Mona) showed those effects for the past oil price returns. Mona was also the only cryptocurrency out of the 39 where the past daily oil price returns had a negative and significant impact on. Despite these negative findings, the daily returns of Bytecoin are positively and significantly affected by the current and past daily oil price returns.

Current daily returns of the S&P500 have a positive and significant effect on 22 out of the 39 altcoins, which is in agreement with the five largest cryptocurrencies from the previous paragraphs. Furthermore, the past daily returns of the S&P500 note a positive and significant impact on three altcoins (EOS, Bytecoin and Decred). The weekly returns of Kyber are negatively affected by the current S&P500 returns, while the daily returns of Salt are negatively affected by the past returns of the S&P500.

Completely in line with the findings from the four largest altcoins, is the impact of the current Bitcoin returns on the daily and weekly returns of the 39 smaller altcoins, with the second model of Verge being

the only model with an insignificant effect. When checking the effects of the previous Bitcoin price returns, the results range from significantly positive to insignificantly negative and everything in between, indicating that this variable does not have a general effect on a majority of the altcoins.

The lagged return of the altcoins itself show widespread results in the Vector-Autoregressive models. The effect of the past weekly returns is negative for Dash, Neo, and Monero for example, while on the contrary, altcoins like NEM, Qtum, and Stellar react positively to their past weekly returns.

The changes in the Google Trends Score in the current and previous period have no consistent effect on a majority of the 39 altcoins unfortunately. The returns of NEM, Iota, Tron, XVG, Vertcoin and HC react positively and significantly to change in the current Google Trends Score, while the returns of Stratis react in a negative and significant way. Overall, this variable does not have a significant impact on the returns of cryptocurrencies.

Model 6 is the model that can explain the returns of the altcoins the best, according to the Adjusted R-squared. Although, the difference in goodness-of-fit with the 4th model is rather small for most of the cryptocurrencies, confirming the previous findings about the inability of the lagged return to explain the current return. The 5th model has the highest Adjusted R-squared of the three daily models by a small fraction, meaning that the current trade volume and the current Bitcoin returns explain the largest part of the returns of the altcoins.

6. Conclusion and discussion

6.1 Conclusion

This paper seeks to explain the factors that affect the returns of 44 of the largest cryptocurrencies. The data ranges from November 4th, 2017 until March 31st, 2020 for the daily data and from October 30th, 2017 until March 30th, 2020 for the weekly data. The factors that were researched in this paper are the changes in trade volume; gold price returns; oil price returns; returns on the S&P500; Bitcoin returns; change in Google Trends Score.

In the first hypothesis, the expectation was that the returns of gold have a positive effect on the returns of the cryptocurrencies. For Bitcoin, only one positive and significant effect was found between the daily gold returns and the returns of Bitcoin the following day. This outcome is in conformance with the research of Jareño et al. (2020), who also found a statistically significant positive relationship in the short run between Bitcoin and gold price returns. Out of the other 43 cryptocurrencies, only a small amount showed a positive and significant of the gold price returns, with other altcoins reacting negatively to an increase of the gold price. These scattered results lead to a rejection of the first hypothesis, meaning that the gold price returns do not have a significant positive effect on the returns of cryptocurrencies.

The hypothesis about the oil price returns forecasted a negative effect between rising oil prices and the returns of cryptocurrencies. As Van Wijk (2013) explained, higher costs for consumers due to higher oil prices would lead to less demand for Bitcoin resulting in a lower price. The previous daily oil price returns showed a negative and significant effect on the Bitcoin returns both models, indicating that a rising oil price yesterday leads to a lower price of Bitcoin today. This result is therefore in line with the theory of Van Wijk (2013) and the regression results of Jareño et al. (2020), who found also found a negative and significant relationship between the oil price and Bitcoin. Contradicting these findings are the results of Ethereum, that show positive and significant effects between the current oil price returns and Ethereum. The other 42 altcoins hardly showed any significant effects, which leads to a rejection of the second hypothesis: there is no evidence that the oil price returns have a negative effect on the majority of cryptocurrencies.

An interesting topic that has been researched by multiple studies, is the effect of the S&P500 on the price of Bitcoin. In this thesis, the Prais-Winsten regressions have shown that there is a positive and significant impact of the current daily gold price returns on the Bitcoin returns. The weekly models also indicate a positive relationship, but this effect is not significant on at least al 10%-level. Ethereum, Ripple, Litecoin and 22 out of the 39 smaller altcoins also show positive and significant in various

models. These positive effects are in line with the research of Liew et al. (2019), who presented a positive correlation between Bitcoin and the S&P500 between January 2015 and February 2018. A similar ARDL-model from Kjaerland et al. (2018) also shows the positive and significant effect of the S&P500 on the returns of Bitcoin, which is confirmed by the ARDL-model in this thesis. These findings lead to an acceptance of the third hypothesis, meaning that the S&P500 has a positive effect on the returns of cryptocurrencies.

Present trade volume has proven to be a positive and significant factor on the returns of all cryptocurrencies in at all models, except for the daily models of two altcoins. These overwhelming results were not found in previous research, although Bouri et al (2019) concluded that trade volume causes price returns of all seven cryptocurrencies in their sample in high quantiles. Opposed to the insignificant findings of past trade volume and Bitcoin returns of Aalborg et al. (2018), do the models 4-6 show that an increase in trade volume in the previous period lead to higher Bitcoin returns in the following period. Ethereum, Ripple, Bitcoin Cash and Litecoin display the same positive relationship between an increase in past volume and current returns, while the smaller altcoins on average do not show signs of a positive relationship. The fourth hypothesis is therefore accepted, there is significant evidence that an increase in trade volume results in higher returns of cryptocurrencies.

The fifth hypothesis was based on the proposition that an increase in Bitcoin returns leads to an increase in the returns of other cryptocurrencies as well. Positive and significant results between the current Bitcoin returns and the altcoin returns were found in every model of all 43 altcoins, except for the second model of Verge. These results are in agreement with the findings of Gandal and Halaburda (2016) and Liew et al. (2019), who displayed positive correlations between Bitcoin and altcoins in certain periods before 2018 already. However, the past returns of Bitcoin did not have a consistent and significant effect on the returns of the other cryptocurrencies in this thesis. The fifth hypothesis is accepted as well, because of the astounding evidence between the current returns of Bitcoin and all other altcoins.

The research of Kristoufek (2015) and Kjaerland et al. (2018) mentioned a positive relationship between Google searches and the price of Bitcoin. Their explanation of this relationship was quite logical: when people's curiosity in Bitcoin increases, the demand and price of Bitcoin would increase as well. Nonetheless, the models in this research do not show significant effects of the change in the Google Trends Score on the returns of Bitcoin or most of the altcoins. Ethereum is one of the few altcoins where the Google Trends Score has a negative and significant on the returns, whilst six smaller cryptocurrencies reacted positively and significantly to an increase of the Google Trends Score. These

results are not coherent enough to accept the final hypothesis, meaning that there is no indication that an increase in the Google Trends Score leads to an increase in returns.

The research question that described the main goal of this paper was the following:

Which model can explain the performance of cryptocurrencies the best?

The results have shown that certain variables have a significant effect on almost all cryptocurrencies that were tested in this research. These variables are trade volume, S&P500 and Bitcoin (for the altcoin-models). Furthermore, six models were used to seek which one could explain the returns of cryptocurrencies the best and the weekly Vector-Autoregressive model has the best goodness-of-fit. The Adjusted R-squared was the highest in model 6 for almost all of the cryptocurrencies, indicating that adding a lagged variable of the returns of the cryptocurrency itself has a positive impact on the explainability of the model.

6.2 Discussion

The results of this thesis fill a gap in the literature about factors that explain the performance of Bitcoin and many other cryptocurrencies. In recent years, the trade volume has been a significant variable determining the results of all cryptocurrencies. The improved accessibility of the whole cryptocurrency market might play an important role as well, because it has become a lot easier to buy and sell cryptocurrencies than multiple years ago. Secondly, this research has shown that the S&P500 has a significant impact on Bitcoin and the majority of altcoins. Earlier research from Kjaerland et al. (2018) and Liew et al. (2019) already showed the relationship between Bitcoin and the S&P500, but the addition of this paper is that there is significant evidence that altcoins are also positively affected by an increase of the stock market. Thirdly, this research adds to the existing literature that the returns of every single altcoin out of the 43 reacted positively on an increase in the returns of Bitcoin, showing that Bitcoin is still the undisputed leader in the cryptocurrency-market today.

The first limitation of this paper is the time period that has been researched. At the end of 2017 and beginning of 2018, Bitcoin and many altcoins noted huge daily price returns combined with a surge in trade volume (over 2000% for some altcoins). It is possible that these exceptional circumstances have influenced the results and that the impact of trade volume on the returns would have been lower if the extreme datapoints were removed. A second limitation is the way the Google Trends Score is used in this paper. Searching on 'Bitcoin cryptocurrency' or 'Dash cryptocurrency' instead of 'Bitcoin' or 'Dash' may have led to different Google Trends Scores but reduces the amount of searches that were meant for other topics with the same name as the cryptocurrency like Dash. A third and final limitation

is the inability to explain the largest part of the Bitcoin returns in the daily and weekly models. The Adjusted R-squared in the Bitcoin models indicates that important explanatory variables (like the amount of daily transactions, daily transaction volume or hash rate) used by Kristoufek (2015) and Aalborg et al. (2018) are missing in these models.

Future research could expand on the foundation that this paper has created on the factors affecting the performance of many cryptocurrencies besides Bitcoin. An interesting topic would be the relationship between the Bitcoin returns and altcoin returns, which could be researched more in depth. Two other variables that could possibly have an impact on the cryptocurrency returns that have not been researched in this paper are the NASDAQ and silver. The S&P500 index contains the 500 largest companies in the United States, while mainly technology stocks are traded on the NASDAQ which show more resemblance to cryptocurrencies. As mentioned in the results of this paper, gold only had significant positive impact on the Bitcoin returns in one model and showed almost no significant results in the regression of the altcoins. A commodity like silver might have more influence on the returns of altcoins as Bitcoin is likely to be the only cryptocurrency that is compared to digital gold. Lastly, specific metrics for each cryptocurrency (daily transactions, new wallets created, transaction volume and increase of the supply) would be an amazing topic for future research, if those metrics are available for multiple altcoins as well.

Another part that could be interesting for future research is the way regressions of the cryptocurrencies are run. In this thesis, six regressions were run for each individual cryptocurrency, but using the approach of Fama and MacBeth (1973) on a regression across all cryptocurrencies could lead to alternative insights. The first step of this method is running a regression with a defined number of factors for each cryptocurrency (similar to this research) to find the beta's, followed by the second step where the impact of the factors on the cryptocurrencies is measured by regressing the returns against the beta's found in the first step.

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8. Appendices

#	Name	Symbol
1	Bitcoin	BTC
2	Ethereum	ETH
3	Bitcoin Cash	BCH
4	Ripple	XRP
5	Litecoin	LTC
6	Dash	DASH
7	Neo	NEO
8	NEM	XEM
9	Monero	XMR
10	Ethereum Classic	ETC
11	Iota	MIOTA
12	OmiseGO	OMG
13	Qtum	QTUM
14	Zcash	ZEC
15	Cardano	ADA
16	Lisk	LSK
17	EOS	EOS
18	Stellar	XLM
19	Waves	WAVES
20	HyperCash	HC
21	Stratis	STRAT
22	Bytecoin	BCN
23	Augur	REP
24	TenX	PAY
25	Golem	GNT
26	BitShares	BTS
27	Binance Coin	BNB
28	MaidSafeCoin	MAID
29	TRON	TRX
30	Basic Attention Token	BAT
31	Kyber Network	KNC
32	Dogecoin	DOGE
33	SALT	SALT
34	Verge	XVG
35	Bitcoin Gold	BTG
36	Icon	ICX
37	Chainlink	LINK
38	Decred	DCR
39	Komodo	KMD
40	Ark	ARK
41	PIVX	PIVX
42	Vertcoin	VTC
43	MonaCoin	MONA
44	Factom	FCT

Appendix 1: Overview of cryptocurrencies used in this research

Table 8. Dash regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0514***	0.302***	0.0524***	0.228***	0.0524***	0.218***
	(0.00425)	(0.0303)	(0.00432)	(0.0323)	(0.00434)	(0.0315)
$VOLUME_{t-1}$			0.00452	-0.0265	0.00323	0.0886**
			(0.00434)	(0.0298)	(0.00470)	(0.0376)
$GOLD_t$	0.240	0.748	0.246	0.495	0.247	0.451
	(0.216)	(0.536)	(0.217)	(0.544)	(0.217)	(0.519)
$GOLD_{t-1}$			-0.381*	0.510	-0.394*	0.533
			(0.219)	(0.518)	(0.219)	(0.527)
OIL_t	0.0454	-0.232	0.0352	-0.392	0.0346	-0.395*
	(0.0595)	(0.200)	(0.0655)	(0.248)	(0.0656)	(0.233)
OIL_{t-1}			-0.0147	-0.0321	-0.0190	-0.0519
			(0.0672)	(0.203)	(0.0674)	(0.196)
$SP500_t$	-0.00948	-0.0820	0.0569	-0.0876	0.0589	-0.108
	(0.137)	(0.435)	(0.146)	(0.429)	(0.146)	(0.402)
$SP500_{t-1}$			0.188	0.0468	0.183	-0.00504
			(0.141)	(0.473)	(0.141)	(0.430)
BTC_t	0.831***	0.785***	0.831***	0.831***	0.831***	0.877***
	(0.0369)	(0.0803)	(0.0373)	(0.0789)	(0.0373)	(0.0771)
BTC_{t-1}			-0.0618*	0.136	-0.0846*	0.416***
			(0.0370)	(0.0827)	(0.0466)	(0.0913)
$DASH_{t-1}$					0.0284	-0.393***
					(0.0340)	(0.0735)
$GOOGLE_t$		0.00132		0.00350		0.00297
		(0.0111)		(0.0103)		(0.0102)
$GOOGLE_{t-1}$				-0.00174		-0.000216
				(0.0103)		(0.0101)
Constant	-0.00259	-0.0223***	-0.00270	-0.0234**	-0.00263	-0.0311**
	(0.00164)	(0.00817)	(0.00165)	(0.00894)	(0.00161)	(0.0126)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4457	0.6631	0.4478	0.6324	0.4472	0.6632
DW (original)	1.965139	2.384483	1.969982	2.186523	2.001826	1.736536
DW (transformed)	1.998425	1.776557	1.998168	1.888772	2.000732	1.953522

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9. NEO regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0606***	0.190***	0.0617***	0.188***	0.0617***	0.188***
	(0.00386)	(0.0312)	(0.00385)	(0.0324)	(0.00387)	(0.0313)
$VOLUME_{t-1}$			0.0132***	0.0371	0.0131***	0.112***
			(0.00385)	(0.0321)	(0.00438)	(0.0328)
$GOLD_t$	0.256	1.061*	0.271	1.196*	0.271	0.912
	(0.202)	(0.628)	(0.202)	(0.697)	(0.202)	(0.658)
$GOLD_{t-1}$			0.0140	0.719	0.0135	0.343
			(0.204)	(0.652)	(0.204)	(0.675)
OIL_t	-0.00368	0.173	0.00460	0.185	0.00456	0.0751
	(0.0559)	(0.243)	(0.0609)	(0.305)	(0.0609)	(0.291)
OIL_{t-1}			0.0456	-0.188	0.0455	-0.111
			(0.0627)	(0.263)	(0.0628)	(0.259)
$SP500_t$	0.182	0.359	0.177	0.172	0.177	0.177
	(0.128)	(0.516)	(0.136)	(0.545)	(0.136)	(0.508)
$SP500_{t-1}$			0.162	0.0767	0.162	0.642
			(0.131)	(0.603)	(0.132)	(0.536)
BTC_t	0.902***	0.805***	0.905***	0.833***	0.905***	0.822***
	(0.0346)	(0.0986)	(0.0348)	(0.104)	(0.0350)	(0.114)
BTC_{t-1}			-0.0567	0.00615	-0.0581	0.583***
			(0.0346)	(0.108)	(0.0461)	(0.128)
NEO_{t-1}					0.00162	-0.608***
					(0.0340)	(0.0890)
$GOOGLE_t$		0.00776		0.00842	-0.00364**	0.00789
		(0.0204)		(0.0210)	(0.00152)	(0.0201)
$GOOGLE_{t-1}$				0.00455		0.00755
				(0.0210)		(0.0198)
Constant	-0.00304**	-0.0156	-0.00365**	-0.0230**	-0.00364**	-0.0275
	(0.00151)	(0.0103)	(0.00151)	(0.0114)	(0.00152)	(0.0231)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5455	0.5703	0.5506	0.5613	0.5501	0.6422
DW (original)	1.997280	2.267465	1.998220	2.289940	1.998948	1.924324
DW (transformed)	1.999371	1.875845	1.998415	1.891549	1.998685	2.015667

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10. NEM regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0456***	0.0488***	0.0445***	0.0560***	0.0446***	0.0525***
	(0.00334)	(0.0175)	(0.00338)	(0.0191)	(0.00338)	(0.0185)
$VOLUME_{t-1}$			-0.000120	0.0262	0.00347	0.0128
			(0.00335)	(0.0194)	(0.00369)	(0.0189)
$GOLD_t$	0.0548	-0.0605	0.123	-0.400	0.118	-0.711
	(0.320)	(0.607)	(0.326)	(0.717)	(0.326)	(0.684)
$GOLD_{t-1}$			-0.523	0.0803	-0.503	-0.242
			(0.330)	(0.714)	(0.330)	(0.636)
OIL_t	0.0285	-0.0824	-0.00335	0.0265	-0.000471	0.332
	(0.0948)	(0.269)	(0.0984)	(0.318)	(0.0984)	(0.299)
OIL_{t-1}			-0.0397	0.0400	-0.0292	-0.172
			(0.102)	(0.267)	(0.102)	(0.252)
$SP500_t$	0.258	0.405	0.369*	0.0325	0.357	-0.111
	(0.209)	(0.519)	(0.221)	(0.560)	(0.221)	(0.525)
$SP500_{t-1}$			0.0349	-0.803	0.0661	-1.085*
			(0.212)	(0.607)	(0.212)	(0.603)
BTC_t	0.747***	0.836***	0.723***	0.893***	0.725***	0.841***
	(0.0547)	(0.103)	(0.0559)	(0.108)	(0.0563)	(0.0991)
BTC_{t-1}			0.131**	0.204*	0.178***	-0.247*
			(0.0562)	(0.115)	(0.0621)	(0.126)
NEM_{t-1}					-0.0771**	0.554***
					(0.0340)	(0.0743)
$GOOGLE_t$		0.0200**		0.0184*		0.0181*
		(0.00881)		(0.01000)		(0.00959)
$GOOGLE_{t-1}$				0.00372		-0.00414
				(0.00998)		(0.00963)
Constant	-0.00514**	-0.0188	-0.00505**	-0.0262	-0.00545**	-0.0159
	(0.00207)	(0.0159)	(0.00210)	(0.0171)	(0.00222)	(0.0104)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3095	0.4136	0.3126	0.4344	0.3113	0.6563
DW (original)	2.364418	1.655047	2.376554	1.725580	2.066719	2.152083
DW (transformed)	2.055088	2.059707	2.057793	2.044378	2.035036	2.079941

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Monero regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0294***	0.105***	0.0291***	0.0521**	0.0291***	0.0442*
	(0.00306)	(0.0210)	(0.00307)	(0.0235)	(0.00307)	(0.0226)
$VOLUME_{t-1}$			-0.00271	-0.0113	4.02e-05	0.0316
			(0.00307)	(0.0201)	(0.00324)	(0.0212)
$GOLD_t$	0.316*	0.583	0.374**	0.385	0.376**	0.283
	(0.172)	(0.411)	(0.174)	(0.413)	(0.174)	(0.389)
$GOLD_{t-1}$			-0.240	0.443	-0.212	0.355
			(0.176)	(0.385)	(0.176)	(0.388)
OIL_t	0.0523	0.0728	0.0392	0.00358	0.0404	-0.0267
	(0.0500)	(0.154)	(0.0527)	(0.182)	(0.0526)	(0.175)
OIL_{t-1}			-0.0252	-0.00916	-0.0191	0.00543
			(0.0544)	(0.153)	(0.0543)	(0.146)
$SP500_t$	0.281**	0.331	0.309***	0.259	0.305**	0.319
	(0.112)	(0.332)	(0.119)	(0.317)	(0.118)	(0.301)
$SP500_{t-1}$			0.123	-0.309	0.137	-0.0397
			(0.114)	(0.356)	(0.114)	(0.326)
BTC_t	0.912***	0.895***	0.920***	0.977***	0.921***	1.003***
	(0.0296)	(0.0627)	(0.0301)	(0.0607)	(0.0301)	(0.0603)
BTC_{t-1}			-0.0586**	0.0921	0.0218	0.410***
			(0.0299)	(0.0666)	(0.0430)	(0.0857)
XMR_{t-1}					-0.0924***	-0.382***
					(0.0337)	(0.0729)
$GOOGLE_t$		0.00549		-0.00823		-0.00883
		(0.0109)		(0.0105)		(0.00991)
$GOOGLE_{t-1}$				-0.0219**		-0.0271***
				(0.0106)		(0.00962)
Constant	-0.00144	-0.00827	-0.00121	-0.00351	-0.00132	-0.00484
	(0.00116)	(0.00638)	(0.00118)	(0.00664)	(0.00127)	(0.00956)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5706	0.7146	0.5721	0.7376	0.5743	0.7521
DW (original)	2.245766	2.411338	2.215311	2.223782	1.993081	1.777988
DW (transformed)	2.022066	1.834766	2.001753	1.922621	1.985892	1.975939

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Ethereum Classic regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0579***	0.158***	0.0583***	0.180***	0.0584***	0.178***
	(0.00406)	(0.0166)	(0.00408)	(0.0193)	(0.00410)	(0.0198)
$VOLUME_{t-1}$			0.00470	-0.00370	0.00603	-0.0235
			(0.00406)	(0.0170)	(0.00452)	(0.0235)
$GOLD_t$	-0.170	0.0464	-0.135	0.211	-0.135	0.172
	(0.206)	(0.453)	(0.206)	(0.499)	(0.207)	(0.502)
$GOLD_{t-1}$			-0.341	1.126**	-0.344	1.115**
			(0.209)	(0.483)	(0.209)	(0.481)
OIL_t	0.0977*	0.0728	0.0905	0.300	0.0909	0.321
	(0.0581)	(0.184)	(0.0623)	(0.220)	(0.0623)	(0.223)
OIL_{t-1}			0.00111	-0.162	0.00502	-0.144
			(0.0642)	(0.185)	(0.0643)	(0.186)
$SP500_t$	0.341***	0.128	0.374***	-0.0743	0.373***	-0.0785
	(0.132)	(0.385)	(0.140)	(0.403)	(0.140)	(0.404)
$SP500_{t-1}$			0.190	-0.330	0.197	-0.436
			(0.134)	(0.432)	(0.135)	(0.436)
BTC_t	0.843***	0.795***	0.848***	0.786***	0.848***	0.785***
	(0.0352)	(0.0723)	(0.0354)	(0.0743)	(0.0356)	(0.0750)
BTC_{t-1}			-0.1000***	-0.0866	-0.0816*	-0.182*
			(0.0353)	(0.0781)	(0.0455)	(0.105)
ETC_{t-1}					-0.0228	0.124
					(0.0340)	(0.0937)
$GOOGLE_t$		-0.000107		-0.000868		-0.000857
		(0.00120)		(0.00126)		(0.00129)
$GOOGLE_{t-1}$				0.00169		0.00175
				(0.00123)		(0.00124)
Constant	-0.00235	-0.0149	-0.00250*	-0.0199**	-0.00255*	-0.0175*
	(0.00148)	(0.00905)	(0.00149)	(0.00967)	(0.00153)	(0.00906)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4905	0.6779	0.4941	0.6952	0.4946	0.7066
DW (original)	2.080481	2.110437	2.076959	2.220215	2.002250	2.037966
DW (transformed)	2.006532	1.979219	2.002417	1.994616	1.998145	2.005508

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12. IOTA regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0327***	0.197***	0.0347***	0.168***	0.0348***	0.169***
	(0.00354)	(0.0205)	(0.00353)	(0.0217)	(0.00356)	(0.0223)
VOLUME$_{t-1}$			0.0151***	0.0161	0.0125***	0.0251
			(0.00353)	(0.0206)	(0.00373)	(0.0282)
GOLD$_t$	-0.258	0.516	-0.267	0.436	-0.255	0.453
	(0.245)	(0.581)	(0.244)	(0.622)	(0.244)	(0.625)
GOLD$_{t-1}$			-0.133	0.993*	-0.109	1.013*
			(0.246)	(0.584)	(0.247)	(0.597)
OIL$_t$	-0.0684	-0.107	-0.0881	-0.182	-0.0908	-0.184
	(0.0678)	(0.232)	(0.0735)	(0.270)	(0.0737)	(0.272)
OIL$_{t-1}$			-0.0357	0.255	-0.0396	0.245
			(0.0758)	(0.230)	(0.0760)	(0.231)
SP500$_t$	0.390**	0.350	0.457***	0.357	0.469***	0.364
	(0.156)	(0.480)	(0.165)	(0.476)	(0.166)	(0.478)
SP500$_{t-1}$			0.189	-0.527	0.134	-0.484
			(0.159)	(0.524)	(0.160)	(0.525)
BTC$_t$	0.956***	0.821***	0.957***	0.904***	0.953***	0.912***
	(0.0418)	(0.0971)	(0.0419)	(0.0994)	(0.0419)	(0.101)
BTC$_{t-1}$			-0.00275	-0.0597	-0.0905*	-0.0265
			(0.0416)	(0.101)	(0.0526)	(0.122)
IOTA$_{t-1}$					0.0964***	-0.0493
					(0.0337)	(0.0982)
GOOGLE$_t$		0.0374*		0.0490**		0.0491**
		(0.0199)		(0.0196)		(0.0197)
GOOGLE$_{t-1}$				0.00711		0.00962
				(0.0196)		(0.0200)
Constant	-0.00212	-0.0250**	-0.00354*	-0.0306***	-0.00342**	-0.0321***
	(0.00184)	(0.0104)	(0.00184)	(0.0106)	(0.00169)	(0.0115)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4307	0.745	0.4416	0.7392	0.4513	0.7312
DW (original)	1.990595	2.055336	2.014150	2.173564	2.013557	2.059427
DW (transformed)	1.995198	1.931729	1.992768	2.040981	2.000316	2.022711

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 13. QTUM regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0527***	0.273***	0.0568***	0.328***	0.0570***	0.332***
	(0.00361)	(0.0277)	(0.00373)	(0.0307)	(0.00374)	(0.0306)
$VOLUME_{t-1}$			0.0131***	0.0882***	0.00966**	0.0390
			(0.00371)	(0.0276)	(0.00417)	(0.0382)
$GOLD_t$	0.132	0.133	0.174	0.832	0.172	0.707
	(0.240)	(0.647)	(0.241)	(0.735)	(0.240)	(0.746)
$GOLD_{t-1}$			0.0347	1.154	0.0225	1.029
			(0.243)	(0.714)	(0.243)	(0.702)
OIL_t	0.0244	-0.415	0.00502	-0.502	0.00362	-0.494
	(0.0645)	(0.293)	(0.0723)	(0.330)	(0.0725)	(0.333)
OIL_{t-1}			-0.0435	-0.0110	-0.0479	0.0587
			(0.0744)	(0.281)	(0.0747)	(0.282)
$SP500_t$	0.212	0.592	0.245	0.386	0.250	0.392
	(0.150)	(0.562)	(0.162)	(0.596)	(0.162)	(0.601)
$SP500_{t-1}$			0.111	0.171	0.0999	-0.0100
			(0.157)	(0.631)	(0.157)	(0.635)
BTC_t	0.974***	0.926***	0.957***	0.884***	0.958***	0.889***
	(0.0414)	(0.109)	(0.0418)	(0.110)	(0.0419)	(0.110)
BTC_{t-1}			-0.119***	-0.0528	-0.190***	-0.219
			(0.0417)	(0.114)	(0.0525)	(0.137)
$QTUM_{t-1}$					0.0765**	0.196**
					(0.0336)	(0.0899)
$GOOGLE_t$		-0.00237		-0.00460		-0.00525
		(0.00599)		(0.00650)		(0.00648)
$GOOGLE_{t-1}$				0.00129		0.000161
				(0.00659)		(0.00657)
Constant	-0.00399**	-0.0281	-0.00508**	-0.0417**	-0.00484***	-0.0346**
	(0.00198)	(0.0170)	(0.00198)	(0.0165)	(0.00185)	(0.0146)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5133	0.5944	0.5199	0.6361	0.5176	0.6571
DW (original)	1.820091	1.668811	1.834581	1.849717	1.994557	2.054478
DW (transformed)	1.986015	1.909247	1.982813	1.957931	1.996704	2.015784

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14. OmiseGo regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0323***	0.218***	0.0340***	0.235***	0.0341***	0.218***
	(0.00361)	(0.0295)	(0.00367)	(0.0313)	(0.00368)	(0.0307)
$VOLUME_{t-1}$			0.00896**	0.0389	0.00806**	0.0803**
			(0.00367)	(0.0304)	(0.00385)	(0.0366)
$GOLD_t$	0.103	0.735	0.128	0.966*	0.128	0.970*
	(0.206)	(0.495)	(0.207)	(0.549)	(0.207)	(0.537)
$GOLD_{t-1}$			-0.0438	0.562	-0.0521	0.645
			(0.209)	(0.526)	(0.209)	(0.551)
OIL_t	0.0621	0.264	0.0686	0.354	0.0680	0.271
	(0.0565)	(0.202)	(0.0623)	(0.244)	(0.0624)	(0.242)
OIL_{t-1}			0.0159	-0.337	0.0117	-0.216
			(0.0642)	(0.209)	(0.0643)	(0.213)
$SP500_t$	0.325**	0.0714	0.339**	0.0767	0.343**	0.0548
	(0.130)	(0.420)	(0.139)	(0.441)	(0.140)	(0.432)
$SP500_{t-1}$			0.119	0.374	0.110	0.550
			(0.135)	(0.477)	(0.135)	(0.447)
BTC_t	0.933***	0.800***	0.930***	0.820***	0.930***	0.832***
	(0.0356)	(0.0834)	(0.0359)	(0.0846)	(0.0360)	(0.0898)
BTC_{t-1}			-0.106***	-0.177*	-0.144***	0.168
			(0.0356)	(0.0922)	(0.0474)	(0.116)
OMG_{t-1}					0.0431	-0.374***
					(0.0339)	(0.0903)
$GOOGLE_t$		-0.00551*		-0.00645**		-0.00531
		(0.00305)		(0.00319)		(0.00330)
$GOOGLE_{t-1}$				-0.00136		-0.00164
				(0.00313)		(0.00323)
Constant	-0.00330**	-0.0153	-0.00377**	-0.0191*	-0.00367**	-0.0259
	(0.00161)	(0.00995)	(0.00161)	(0.0111)	(0.00156)	(0.0167)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5080	0.6471	0.5120	0.6567	0.5089	0.6986
DW (original)	1.922267	2.061030	1.932171	2.109996	1.999688	1.979530
DW (transformed)	1.991746	1.939541	1.990067	1.961771	1.998738	1.954042

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15. ZCASH regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0294***	0.155***	0.0298***	0.146***	0.0299***	0.143***
	(0.00337)	(0.0228)	(0.00335)	(0.0232)	(0.00335)	(0.0230)
$VOLUME_{t-1}$			0.00779**	-0.00415	0.00629*	0.0250
			(0.00337)	(0.0239)	(0.00352)	(0.0278)
$GOLD_t$	0.203	0.609	0.270	0.626	0.276	0.575
	(0.200)	(0.560)	(0.201)	(0.621)	(0.201)	(0.623)
$GOLD_{t-1}$			-0.369*	0.431	-0.388*	0.384
			(0.202)	(0.596)	(0.202)	(0.612)
OIL_t	0.0516	-0.129	0.0312	-0.298	0.0283	-0.293
	(0.0561)	(0.224)	(0.0603)	(0.276)	(0.0605)	(0.274)
OIL_{t-1}			0.00428	0.115	-0.00613	0.0944
			(0.0622)	(0.230)	(0.0623)	(0.230)
$SP500_t$	-0.0772	0.150	-0.00190	0.196	0.00624	0.189
	(0.128)	(0.464)	(0.135)	(0.486)	(0.136)	(0.483)
$SP500_{t-1}$			0.330**	0.0110	0.339***	0.0408
			(0.130)	(0.530)	(0.130)	(0.515)
BTC_t	0.818***	0.738***	0.820***	0.786***	0.818***	0.802***
	(0.0343)	(0.0900)	(0.0345)	(0.0926)	(0.0345)	(0.0946)
BTC_{t-1}			-0.0552	0.0504	-0.105**	0.216*
			(0.0343)	(0.0975)	(0.0439)	(0.117)
$ZCASH_{t-1}$					0.0665**	-0.210**
					(0.0336)	(0.0915)
$GOOGLE_t$		0.00290		0.00308		0.00289
		(0.00515)		(0.00520)		(0.00520)
$GOOGLE_{t-1}$				0.000300		0.00106
				(0.00520)		(0.00517)
Constant	-0.00271*	-0.0230**	-0.00301**	-0.0267**	-0.00287**	-0.0309**
	(0.00145)	(0.0102)	(0.00145)	(0.0115)	(0.00137)	(0.0139)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4435	0.563	0.4506	0.5417	0.4525	0.5635
DW (original)	2.057418	2.126559	2.068999	2.058179	2.011573	1.898952
DW (transformed)	2.000793	1.935888	2.000733	1.967591	2.006849	1.962980

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Cardano regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0527***	0.224***	0.0539***	0.208***	0.0507***	0.165***
	(0.00440)	(0.0251)	(0.00440)	(0.0263)	(0.00420)	(0.0205)
$VOLUME_{t-1}$			0.0155***	0.00992	0.00499	0.0170
			(0.00440)	(0.0261)	(0.00456)	(0.0262)
$GOLD_t$	0.0759	0.498	0.0774	0.400	0.178	-0.763
	(0.332)	(1.391)	(0.333)	(1.565)	(0.322)	(1.228)
$GOLD_{t-1}$			-0.132	-1.273	-0.190	-1.112
			(0.337)	(1.459)	(0.328)	(1.292)
OIL_t	0.0520	0.00569	0.0463	0.111	0.0346	-0.449
	(0.0918)	(0.561)	(0.101)	(0.713)	(0.0982)	(0.595)
OIL_{t-1}			0.0116	-0.296	-0.0376	0.146
			(0.104)	(0.590)	(0.101)	(0.522)
$SP500_t$	0.541**	0.649	0.571**	-0.0335	0.563**	1.457
	(0.211)	(1.165)	(0.226)	(1.214)	(0.222)	(0.947)
$SP500_{t-1}$			0.200	-0.0360	0.0387	0.785
			(0.217)	(1.364)	(0.212)	(0.981)
BTC_t	0.914***	1.068***	0.923***	0.970***	0.894***	1.051***
	(0.0573)	(0.228)	(0.0577)	(0.238)	(0.0558)	(0.202)
BTC_{t-1}			-0.0113	0.518**	-0.353***	0.975***
			(0.0573)	(0.245)	(0.0619)	(0.203)
ADA_{t-1}					0.407***	-0.605***
					(0.0302)	(0.0661)
$GOOGLE_t$		0.0187		0.0212		-0.00746
		(0.0411)		(0.0447)		(0.0341)
$GOOGLE_{t-1}$				0.0132		-0.0657**
				(0.0436)		(0.0329)
Constant	-0.00243	-0.0157	-0.00402	-0.0190	-0.00389**	0.0371
	(0.00254)	(0.0253)	(0.00250)	(0.0257)	(0.00177)	(0.0825)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3515	0.5406	0.3584	0.5512	0.4929	0.7812
DW (original)	1.966849	2.211819	2.032517	2.094791	2.068214	1.863198
DW (transformed)	2.003009	1.943886	1.994880	1.881881	2.083544	1.865665

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Lisk regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0431***	0.256***	0.0427***	0.247***	0.0427***	0.249***
	(0.00337)	(0.0287)	(0.00341)	(0.0303)	(0.00343)	(0.0335)
$VOLUME_{t-1}$			0.00125	0.0416	0.000655	0.0566
			(0.00342)	(0.0305)	(0.00374)	(0.0402)
$GOLD_t$	-0.142	0.702	-0.107	0.418	-0.108	0.460
	(0.226)	(0.662)	(0.228)	(0.759)	(0.228)	(0.767)
$GOLD_{t-1}$			-0.126	0.266	-0.125	0.307
			(0.229)	(0.702)	(0.229)	(0.716)
OIL_t	-0.0310	-0.0566	-0.0352	0.0567	-0.0350	0.0714
	(0.0607)	(0.266)	(0.0686)	(0.324)	(0.0687)	(0.338)
OIL_{t-1}			-0.0386	-0.198	-0.0385	-0.213
			(0.0703)	(0.276)	(0.0705)	(0.278)
$SP500_t$	0.399***	0.354	0.401***	0.409	0.401***	0.399
	(0.141)	(0.557)	(0.153)	(0.582)	(0.153)	(0.585)
$SP500_{t-1}$			-0.0114	0.0912	-0.0182	0.131
			(0.148)	(0.637)	(0.149)	(0.636)
BTC_t	0.846***	0.647***	0.829***	0.680***	0.829***	0.684***
	(0.0387)	(0.106)	(0.0392)	(0.111)	(0.0393)	(0.115)
BTC_{t-1}			-0.133***	-0.167	-0.145***	-0.130
			(0.0389)	(0.113)	(0.0483)	(0.130)
$LISK_{t-1}$					0.0156	-0.0712
					(0.0340)	(0.107)
$GOOGLE_t$		-0.00187		-0.00225		-0.00225
		(0.00356)		(0.00366)		(0.00367)
$GOOGLE_{t-1}$				-0.00368		-0.00384
				(0.00368)		(0.00369)
Constant	-0.00305	-0.0150	-0.00294	-0.0118	-0.00290	-0.0127
	(0.00188)	(0.0129)	(0.00191)	(0.0153)	(0.00188)	(0.0162)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4581	0.5390	0.4639	0.5276	0.4616	0.5148
DW (original)	1.808322	2.121577	1.791826	2.137734	1.965212	1.996289
DW (transformed)	1.983176	1.982969	1.977677	1.994140	1.980325	1.990367

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18. EOS regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0600***	0.225***	0.0605***	0.233***	0.0604***	0.222***
	(0.00375)	(0.0262)	(0.00377)	(0.0256)	(0.00378)	(0.0258)
VOLUME$_{t-1}$			0.00537	0.0708***	0.00112	0.0387
			(0.00378)	(0.0262)	(0.00432)	(0.0344)
GOLD$_t$	0.0696	-0.0338	0.0871	0.349	0.0974	0.278
	(0.231)	(0.571)	(0.233)	(0.618)	(0.233)	(0.613)
GOLD$_{t-1}$			-0.308	0.664	-0.345	0.593
			(0.235)	(0.576)	(0.235)	(0.564)
OIL$_t$	-0.00723	-0.278	-0.000991	-0.303	-0.00316	-0.277
	(0.0646)	(0.239)	(0.0701)	(0.273)	(0.0703)	(0.275)
OIL$_{t-1}$			0.0736	0.301	0.0693	0.308
			(0.0723)	(0.234)	(0.0725)	(0.233)
SP500$_t$	0.178	0.413	0.201	0.300	0.208	0.224
	(0.148)	(0.491)	(0.158)	(0.492)	(0.158)	(0.483)
SP500$_{t-1}$			0.263*	-0.152	0.251*	-0.253
			(0.152)	(0.542)	(0.152)	(0.541)
BTC$_t$	0.991***	0.986***	0.995***	1.044***	0.993***	1.039***
	(0.0396)	(0.0945)	(0.0401)	(0.0927)	(0.0401)	(0.0916)
BTC$_{t-1}$			-0.0331	-0.115	-0.107**	-0.282**
			(0.0397)	(0.0984)	(0.0519)	(0.122)
EOS$_{t-1}$					0.0774**	0.188**
					(0.0338)	(0.0891)
GOOGLE$_t$		0.00793		0.0141		0.0141
		(0.0141)		(0.0145)		(0.0146)
GOOGLE$_{t-1}$				-0.0000674		-0.00486
				(0.0146)		(0.0147)
Constant	-0.00116	-0.00742	-0.00134	-0.0202*	-0.00127	-0.0178*
	(0.00170)	(0.0111)	(0.00171)	(0.0107)	(0.00160)	(0.00969)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5224	0.6941	0.5237	0.7372	0.5271	0.7634
DW (original)	2.037321	2.013850	2.042725	2.265245	2.006232	2.189740
DW (transformed)	2.000532	1.947849	1.996777	2.040198	2.001352	2.126975

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19. Stellar regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0569***	0.136***	0.0580***	0.121***	0.0580***	0.115***
	(0.00377)	(0.0198)	(0.00380)	(0.0204)	(0.00383)	(0.0197)
$VOLUME_{t-1}$			0.00735*	-0.0397*	0.00400	-0.0346
			(0.00380)	(0.0218)	(0.00430)	(0.0235)
$GOLD_t$	0.174	-0.209	0.177	-0.915	0.184	-0.544
	(0.225)	(0.593)	(0.226)	(0.725)	(0.226)	(0.694)
$GOLD_{t-1}$			-0.00599	-0.285	-0.0257	0.191
			(0.228)	(0.720)	(0.229)	(0.634)
OIL_t	0.0643	0.0948	0.0501	0.124	0.0484	0.265
	(0.0625)	(0.268)	(0.0682)	(0.311)	(0.0683)	(0.307)
OIL_{t-1}			-0.00488	-0.173	-0.0134	-0.121
			(0.0703)	(0.268)	(0.0704)	(0.254)
$SP500_t$	0.429***	0.650	0.462***	0.552	0.465***	0.284
	(0.143)	(0.511)	(0.153)	(0.552)	(0.153)	(0.520)
$SP500_{t-1}$			0.207	-0.316	0.180	-1.011*
			(0.147)	(0.584)	(0.148)	(0.602)
BTC_t	0.842***	1.085***	0.839***	1.171***	0.836***	1.013***
	(0.0385)	(0.106)	(0.0389)	(0.113)	(0.0390)	(0.109)
BTC_{t-1}			-0.0307	0.0787	-0.0962**	-0.508***
			(0.0386)	(0.116)	(0.0481)	(0.131)
XLM_{t-1}					0.0776**	0.603***
					(0.0341)	(0.0778)
$GOOGLE_t$		-0.0192		0.00380		0.0110
		(0.0174)		(0.0207)		(0.0213)
$GOOGLE_{t-1}$				0.0486**		0.0000493
				(0.0209)		(0.0206)
Constant	-0.00183	0.00486	-0.00239	-0.00325	-0.00233	-0.00500
	(0.00167)	(0.0167)	(0.00168)	(0.0191)	(0.00157)	(0.00920)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4768	0.6038	0.4778	0.6217	0.4846	0.7653
DW (original)	2.017055	1.626324	2.034545	1.659089	2.015647	2.063918
DW (transformed)	2.000349	2.086208	1.997756	2.109444	2.010248	2.176824

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20. Waves regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0517***	0.111***	0.0516***	0.117***	0.0516***	0.112***
	(0.00317)	(0.0206)	(0.00320)	(0.0184)	(0.00320)	(0.0183)
$VOLUME_{t-1}$			-0.0000367	0.0389**	0.00329	0.0102
			(0.00322)	(0.0184)	(0.00366)	(0.0209)
$GOLD_t$	9.33e-06	-0.493	0.0213	-0.425	0.0219	-0.649
	(0.213)	(0.496)	(0.214)	(0.523)	(0.214)	(0.520)
$GOLD_{t-1}$			0.187	-0.138	0.201	-0.0817
			(0.216)	(0.501)	(0.216)	(0.482)
OIL_t	-0.0834	0.00264	-0.0802	0.147	-0.0782	0.138
	(0.0590)	(0.222)	(0.0644)	(0.226)	(0.0643)	(0.230)
OIL_{t-1}			0.0121	-0.473**	0.0115	-0.428**
			(0.0665)	(0.197)	(0.0664)	(0.198)
$SP500_t$	0.160	0.505	0.151	0.554	0.148	0.682
	(0.135)	(0.436)	(0.145)	(0.415)	(0.144)	(0.421)
$SP500_{t-1}$			0.159	0.309	0.165	0.125
			(0.139)	(0.461)	(0.139)	(0.461)
BTC_t	0.798***	0.826***	0.797***	0.870***	0.796***	0.832***
	(0.0366)	(0.0859)	(0.0370)	(0.0790)	(0.0371)	(0.0770)
BTC_{t-1}			-0.0898**	-0.163**	-0.0381	-0.339***
			(0.0367)	(0.0806)	(0.0458)	(0.104)
$WAVES_{t-1}$					-0.0648*	0.259***
					(0.0340)	(0.0848)
$GOOGLE_t$		-0.00335		0.000508		0.000442
		(0.00288)		(0.00268)		(0.00273)
$GOOGLE_{t-1}$				0.0107***		0.0104***
				(0.00265)		(0.00264)
Constant	-0.00397**	-0.00938	-0.00391**	-0.0271***	-0.00416**	-0.0223***
	(0.00160)	(0.0126)	(0.00163)	(0.00994)	(0.00174)	(0.00810)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4964	0.5464	0.4979	0.6553	0.5026	0.6967
DW (original)	1.988158	1.839882	1.982696	1.960913	1.986930	2.098127
DW (transformed)	1.993334	2.019861	1.991744	1.992018	1.989821	1.939780

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21. HyperCash regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00214***	0.0153**	0.00218***	0.0167**	0.00218***	0.0167**
	(0.000713)	(0.00745)	(0.000711)	(0.00725)	(0.000712)	(0.00727)
$VOLUME_{t-1}$			-0.000489	-0.00844	-0.000489	-0.00895
			(0.000712)	(0.00730)	(0.000716)	(0.00741)
$GOLD_t$	0.259	0.886	0.309	1.163	0.309	1.156
	(0.317)	(0.791)	(0.318)	(0.860)	(0.318)	(0.865)
$GOLD_{t-1}$			0.0142	1.404*	0.0144	1.350
			(0.322)	(0.821)	(0.322)	(0.824)
OIL_t	0.0570	0.206	0.0682	0.116	0.0682	0.117
	(0.0894)	(0.331)	(0.0961)	(0.373)	(0.0961)	(0.377)
OIL_{t-1}			0.0135	0.249	0.0135	0.244
			(0.0990)	(0.319)	(0.0991)	(0.322)
$SP500_t$	0.358*	-0.580	0.330	-0.868	0.330	-0.879
	(0.203)	(0.666)	(0.215)	(0.668)	(0.216)	(0.671)
$SP500_{t-1}$			0.167	-0.677	0.167	-0.657
			(0.207)	(0.727)	(0.208)	(0.737)
BTC_t	1.038***	0.724***	1.046***	0.803***	1.046***	0.795***
	(0.0543)	(0.127)	(0.0547)	(0.125)	(0.0548)	(0.125)
BTC_{t-1}			-0.191***	0.0993	-0.191***	0.0796
			(0.0543)	(0.129)	(0.0646)	(0.143)
HC_{t-1}					-0.000037	0.0439
					(0.0338)	(0.0884)
$GOOGLE_t$		0.00352***		0.00379***		0.00376***
		(0.00107)		(0.00102)		(0.00103)
$GOOGLE_{t-1}$				0.000397		0.000228
				(0.00102)		(0.00108)
Constant		-0.0167		-0.0248		-0.0239
		(0.0160)		(0.0157)		(0.0152)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3113	0.2727	0.3174	0.3277	0.3166	0.3261
DW (original)	2.081647	1.881619	2.083204	2.019615	2.000450	2.031388
DW (transformed)	1.999066	1.887952	1.999431	2.002021	2.000442	2.010577

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Stratis regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.000889**	0.0563***	0.000871**	0.0557***	0.000870**	0.0571***
	(0.000345)	(0.00558)	(0.000347)	(0.00572)	(0.000347)	(0.00572)
$VOLUME_{t-1}$			0.0000145	-0.000325	-0.00000097	0.0238***
			(0.000347)	(0.00574)	(0.000349)	(0.00764)
$GOLD_t$	-0.00980	0.187	0.0293	0.203	0.0297	0.110
	(0.253)	(0.514)	(0.255)	(0.597)	(0.255)	(0.579)
$GOLD_{t-1}$			0.0887	0.0904	0.0860	0.0965
			(0.257)	(0.562)	(0.258)	(0.582)
OIL_t	-0.0571	0.0969	-0.0917	0.135	-0.0926	0.149
	(0.0704)	(0.211)	(0.0770)	(0.257)	(0.0771)	(0.253)
OIL_{t-1}			-0.0900	0.0257	-0.0917	0.0221
			(0.0792)	(0.220)	(0.0793)	(0.223)
$SP500_t$	0.0585	0.384	0.116	0.308	0.118	0.414
	(0.161)	(0.451)	(0.172)	(0.482)	(0.172)	(0.459)
$SP500_{t-1}$			0.113	-0.174	0.111	0.0922
			(0.166)	(0.518)	(0.166)	(0.478)
BTC_t	1.063***	0.936***	1.056***	0.960***	1.056***	0.937***
	(0.0432)	(0.0857)	(0.0437)	(0.0894)	(0.0438)	(0.0916)
BTC_{t-1}			-0.0502	0.0151	-0.0715	0.328***
			(0.0434)	(0.0921)	(0.0565)	(0.122)
$STRAT_{t-1}$					0.0207	-0.417***
					(0.0340)	(0.0882)
$GOOGLE_t$		-0.00639**		-0.00715**		-0.00593*
		(0.00308)		(0.00330)		(0.00320)
$GOOGLE_{t-1}$				-0.00356		-0.00343
				(0.00334)		(0.00325)
Constant	-0.00146	-0.0174	-0.00157	-0.0129	-0.00154	-0.0254
	(0.00186)	(0.0106)	(0.00187)	(0.0121)	(0.00184)	(0.0184)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4198	0.7071	0.4184	0.7001	0.4170	0.7408
DW (original)	2.022929	2.051009	2.024893	2.064262	2.000446	1.961299
DW (transformed)	1.998940	1.957270	1.997700	1.963405	1.998576	2.026310

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23. Bytecoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0267***	0.0463***	0.0266***	0.0458***	0.0266***	0.0444***
	(0.000667)	(0.00966)	(0.000675)	(0.0110)	(0.000675)	(0.0104)
$VOLUME_{t-1}$			0.000795	-0.00108	0.00371***	0.0164
			(0.000676)	(0.00985)	(0.00112)	(0.0104)
$GOLD_t$	0.463	0.419	0.380	0.472	0.382	0.666
	(0.381)	(0.928)	(0.387)	(1.055)	(0.388)	(1.021)
$GOLD_{t-1}$			0.418	1.521	0.445	1.843*
			(0.393)	(1.026)	(0.393)	(1.061)
OIL_t	0.179	0.416	0.209*	0.467	0.201*	0.191
	(0.114)	(0.383)	(0.117)	(0.460)	(0.117)	(0.456)
OIL_{t-1}			0.223*	0.0906	0.219*	-0.0133
			(0.121)	(0.394)	(0.121)	(0.399)
$SP500_t$	1.175***	0.953	0.931***	0.497	0.951***	0.304
	(0.251)	(0.792)	(0.265)	(0.844)	(0.264)	(0.805)
$SP500_{t-1}$			0.526**	-1.039	0.703***	-0.322
			(0.253)	(0.918)	(0.255)	(0.851)
BTC_t	1.017***	1.045***	1.065***	1.096***	1.064***	1.153***
	(0.0652)	(0.151)	(0.0666)	(0.157)	(0.0667)	(0.165)
BTC_{t-1}			-0.184***	0.174	-0.0731	0.681***
			(0.0663)	(0.163)	(0.0748)	(0.187)
BCN_{t-1}					-0.109***	-0.406***
					(0.0335)	(0.0880)
$GOOGLE_t$		0.00730		0.00578		0.00688
		(0.00744)		(0.00799)		(0.00756)
$GOOGLE_{t-1}$				0.00238		0.00848
				(0.00875)		(0.00812)
Constant	-0.00583**	-0.0127	-0.00593**	-0.0171	-0.00659**	-0.0334
	(0.00241)	(0.0189)	(0.00242)	(0.0221)	(0.00266)	(0.0344)
Observations	878	125	877	124	877	123
Adj. R-squared	0.6809	0.4095	0.6846	0.3989	0.6792	0.4885
DW (original)	2.391620	2.048488	2.392912	1.985683	2.010371	1.930903
DW (transformed)	2.008561	1.985127	2.007760	1.982752	2.000796	2.004305

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24. Augur regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0170***	0.0753***	0.0167***	0.0766***	0.0168***	0.0757***
	(0.00136)	(0.00649)	(0.00136)	(0.00664)	(0.00137)	(0.00655)
$VOLUME_{t-1}$			-0.00303**	-0.00272	-0.000879	-0.0257***
			(0.00136)	(0.00665)	(0.00149)	(0.00930)
$GOLD_t$	0.0126	0.788	-0.00217	0.662	-0.00178	0.626
	(0.279)	(0.570)	(0.280)	(0.646)	(0.280)	(0.642)
$GOLD_{t-1}$			-0.142	-0.00417	-0.133	-0.201
			(0.283)	(0.619)	(0.282)	(0.599)
OIL_t	0.0929	0.218	0.105	0.295	0.101	0.336
	(0.0758)	(0.238)	(0.0842)	(0.286)	(0.0835)	(0.286)
OIL_{t-1}			0.0756	-0.168	0.0839	-0.208
			(0.0866)	(0.249)	(0.0858)	(0.248)
$SP500_t$	0.377**	0.0180	0.414**	0.00605	0.416**	-0.0310
	(0.176)	(0.491)	(0.188)	(0.524)	(0.187)	(0.514)
$SP500_{t-1}$			0.350*	-0.284	0.385**	-0.612
			(0.182)	(0.569)	(0.182)	(0.576)
BTC_t	0.807***	0.682***	0.808***	0.667***	0.806***	0.606***
	(0.0476)	(0.0915)	(0.0481)	(0.0990)	(0.0483)	(0.0966)
BTC_{t-1}			-0.0886*	0.0373	0.00845	-0.0723
			(0.0477)	(0.0978)	(0.0550)	(0.111)
$AUGUR_{t-1}$					-0.126***	0.307***
					(0.0337)	(0.0897)
$GOOGLE_t$		0.000146		-0.000132		-0.000437
		(0.00213)		(0.00226)		(0.00226)
$GOOGLE_{t-1}$				0.00260		0.00360
				(0.00231)		(0.00228)
Constant		-0.0171		-0.0239*		-0.0195*
		(0.0118)		(0.0134)		(0.0109)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3461	0.6216	0.3528	0.6190	0.3754	0.6628
DW (original)	1.877949	2.059731	1.868720	2.108615	1.992153	2.021947
DW (transformed)	2.000537	1.973443	2.001472	1.987196	1.995664	2.053529

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 25. TenX regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00281***	0.136***	0.00301***	0.139***	0.00300***	0.140***
	(0.000966)	(0.0195)	(0.000978)	(0.0204)	(0.000979)	(0.0206)
$VOLUME_{t-1}$			0.000566	-0.0332	0.000516	-0.0139
			(0.000978)	(0.0208)	(0.000983)	(0.0252)
$GOLD_t$	-0.183	-0.288	-0.180	0.229	-0.180	0.228
	(0.304)	(1.008)	(0.307)	(1.150)	(0.308)	(1.152)
$GOLD_{t-1}$			0.173	0.559	0.170	0.640
			(0.310)	(1.090)	(0.310)	(1.109)
OIL_t	-0.00439	0.656	0.00559	0.512	0.00572	0.566
	(0.0829)	(0.397)	(0.0926)	(0.496)	(0.0928)	(0.494)
OIL_{t-1}			0.0473	0.129	0.0480	0.158
			(0.0953)	(0.423)	(0.0954)	(0.427)
$SP500_t$	0.296	1.134	0.322	1.539*	0.322	1.453
	(0.192)	(0.857)	(0.207)	(0.907)	(0.207)	(0.918)
$SP500_{t-1}$			0.294	-0.0841	0.290	0.0568
			(0.200)	(0.988)	(0.201)	(0.993)
BTC_t	0.830***	0.603***	0.828***	0.636***	0.828***	0.639***
	(0.0520)	(0.157)	(0.0528)	(0.166)	(0.0528)	(0.169)
BTC_{t-1}			-0.0693	-0.0985	-0.0797	-0.0385
			(0.0523)	(0.170)	(0.0594)	(0.186)
$TENX_{t-1}$					0.0132	-0.127
					(0.0340)	(0.0955)
$GOOGLE_t$		-0.00297		-0.00316		-0.00318
		(0.00470)		(0.00483)		(0.00483)
$GOOGLE_{t-1}$				-0.00451		-0.00587
				(0.00486)		(0.00488)
Constant	-0.00315	-0.0319*	-0.00332	-0.0206	-0.00327	-0.0241
	(0.00241)	(0.0188)	(0.00245)	(0.0218)	(0.00242)	(0.0240)
Observations	878	126	877	125	877	125
Adj. R-squared	0.2406	0.395	0.2401	0.3534	0.2385	0.3621
DW (original)	1.885480	2.298580	1.881179	2.238157	1.987461	2.017454
DW (transformed)	1.992282	2.057172	1.991282	2.044501	1.992964	2.009481

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26. Golem regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00192***	0.0580***	0.00190***	0.0603***	0.00190***	0.0601***
	(0.000454)	(0.00827)	(0.000453)	(0.00833)	(0.000453)	(0.00839)
$VOLUME_{t-1}$			-0.000316	0.0182**	-0.000290	0.0215**
			(0.000453)	(0.00832)	(0.000458)	(0.0100)
$GOLD_t$	0.227	0.332	0.200	0.183	0.199	0.180
	(0.263)	(0.586)	(0.263)	(0.675)	(0.263)	(0.676)
$GOLD_{t-1}$			-0.791***	0.785	-0.787***	0.802
			(0.266)	(0.665)	(0.266)	(0.673)
OIL_t	0.101	0.182	0.131*	0.297	0.131*	0.290
	(0.0731)	(0.257)	(0.0795)	(0.297)	(0.0795)	(0.298)
OIL_{t-1}			0.113	-0.00719	0.116	-0.0129
			(0.0819)	(0.254)	(0.0820)	(0.256)
$SP500_t$	0.579***	-0.198	0.586***	-0.400	0.585***	-0.382
	(0.167)	(0.500)	(0.178)	(0.528)	(0.178)	(0.531)
$SP500_{t-1}$			0.0374	-0.792	0.0461	-0.786
			(0.171)	(0.566)	(0.173)	(0.564)
BTC_t	0.870***	0.943***	0.885***	1.010***	0.885***	1.012***
	(0.0449)	(0.0984)	(0.0452)	(0.100)	(0.0453)	(0.103)
BTC_{t-1}			0.0211	-0.0179	0.0326	0.0310
			(0.0450)	(0.104)	(0.0537)	(0.132)
$GOLEM_{t-1}$					-0.0132	-0.0600
					(0.0338)	(0.0936)
$GOOGLE_t$		0.00132		0.00133		0.00135
		(0.00704)		(0.00765)		(0.00768)
$GOOGLE_{t-1}$				-0.00282		-0.00252
				(0.00762)		(0.00760)
Constant	-0.00119	-0.0158	-0.000643	-0.0229	-0.000658	-0.0241
	(0.00194)	(0.0143)	(0.00196)	(0.0160)	(0.00199)	(0.0170)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3326	0.5640	0.3372	0.5848	0.3368	0.5840
DW (original)	2.015053	1.765043	2.012283	1.734455	1.998020	1.938421
DW (transformed)	2.000293	1.972722	2.000247	1.963040	1.998857	1.951919

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 27. BitShares regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0165***	0.0794***	0.0167***	0.0807***	0.0166***	0.0810***
	(0.00197)	(0.0149)	(0.00199)	(0.0152)	(0.00199)	(0.0153)
$VOLUME_{t-1}$			0.00170	0.0164	-0.00169	0.0115
			(0.00199)	(0.0153)	(0.00206)	(0.0177)
$GOLD_t$	-0.0435	0.134	-0.0300	0.0150	-0.0156	-0.0377
	(0.242)	(0.630)	(0.243)	(0.751)	(0.243)	(0.764)
$GOLD_{t-1}$			-0.122	0.0511	-0.138	-0.0138
			(0.246)	(0.734)	(0.247)	(0.733)
OIL_t	0.105	0.255	0.122*	0.304	0.116	0.295
	(0.0666)	(0.284)	(0.0734)	(0.320)	(0.0736)	(0.323)
OIL_{t-1}			0.0322	0.00153	-0.00609	-0.0210
			(0.0756)	(0.277)	(0.0761)	(0.279)
$SP500_t$	0.289*	0.326	0.268	0.0614	0.286*	0.0748
	(0.153)	(0.551)	(0.164)	(0.603)	(0.166)	(0.610)
$SP500_{t-1}$			0.0235	-0.344	-0.0280	-0.353
			(0.159)	(0.611)	(0.159)	(0.620)
BTC_t	0.930***	0.943***	0.929***	1.036***	0.924***	1.037***
	(0.0413)	(0.108)	(0.0418)	(0.112)	(0.0417)	(0.115)
BTC_{t-1}			-0.0835**	0.0552	-0.286***	0.00377
			(0.0415)	(0.114)	(0.0512)	(0.139)
BTS_{t-1}					0.232***	0.0643
					(0.0330)	(0.0922)
$GOOGLE_t$		-0.00117		-0.000677		-0.000752
		(0.00300)		(0.00311)		(0.00314)
$GOOGLE_{t-1}$				0.000519		0.000478
				(0.00321)		(0.00324)
Constant	-0.00217	-0.00394	-0.00231	-0.0139	-0.00189	-0.0132
	(0.00186)	(0.0177)	(0.00190)	(0.0198)	(0.00154)	(0.0188)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4080	0.4836	0.4082	0.5233	0.4285	0.5177
DW (original)	1.945684	1.493174	1.942760	1.546516	1.999504	1.920795
DW (transformed)	2.002548	1.879041	2.001522	1.930503	1.996830	1.951335

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 28. Binance Coin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0668***	0.132***	0.0693***	0.173***	0.0701***	0.189***
	(0.00404)	(0.0296)	(0.00413)	(0.0368)	(0.00415)	(0.0358)
$VOLUME_{t-1}$			0.0128***	0.0240	-0.00124	0.00215
			(0.00411)	(0.0310)	(0.00474)	(0.0345)
$GOLD_t$	0.0305	0.321	0.0293	0.124	0.0318	0.0233
	(0.197)	(0.700)	(0.201)	(0.853)	(0.201)	(0.841)
$GOLD_{t-1}$			-0.0767	-0.0308	-0.127	-0.254
			(0.203)	(0.838)	(0.203)	(0.767)
OIL_t	0.0618	0.0310	0.0401	0.0814	0.0417	0.103
	(0.0519)	(0.314)	(0.0601)	(0.372)	(0.0607)	(0.370)
OIL_{t-1}			-0.0293	0.173	-0.0345	0.0152
			(0.0619)	(0.319)	(0.0627)	(0.308)
$SP500_t$	0.450***	0.313	0.491***	0.147	0.502***	0.0479
	(0.122)	(0.609)	(0.135)	(0.669)	(0.136)	(0.643)
$SP500_{t-1}$			0.0727	-0.642	0.000575	-0.660
			(0.131)	(0.729)	(0.132)	(0.729)
BTC_t	0.823***	0.950***	0.822***	0.873***	0.822***	0.844***
	(0.0341)	(0.120)	(0.0351)	(0.131)	(0.0350)	(0.135)
BTC_{t-1}			-0.0161	0.160	-0.203***	-0.230
			(0.0347)	(0.132)	(0.0440)	(0.145)
BNB_{t-1}					0.226***	0.442***
					(0.0329)	(0.0900)
$GOOGLE_t$		-0.00647		-0.00732		-0.00608
		(0.00581)		(0.00695)		(0.00685)
$GOOGLE_{t-1}$				0.000809		0.00198
				(0.00694)		(0.00671)
Constant	0.000459	0.0191	-0.000235	0.0164	-0.000420	0.00318
	(0.00183)	(0.0192)	(0.00183)	(0.0216)	(0.00144)	(0.0153)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5538	0.4217	0.5559	0.4102	0.5617	0.5574
DW (original)	1.637318	1.626496	1.648750	1.818010	2.007456	2.120491
DW (transformed)	1.996877	2.006681	1.996621	1.968562	2.002375	2.101176

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 29. MaidSafeCoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00325	0.101***	0.00442	0.0917**	0.00439	0.0933**
	(0.00395)	(0.0370)	(0.00411)	(0.0386)	(0.00411)	(0.0392)
$VOLUME_{t-1}$			0.00210	0.0616	0.00217	0.0705*
			(0.00410)	(0.0377)	(0.00410)	(0.0389)
$GOLD_t$	0.389	1.132*	0.439*	1.403**	0.442*	1.443**
	(0.247)	(0.592)	(0.247)	(0.635)	(0.248)	(0.636)
$GOLD_{t-1}$			0.281	0.0553	0.297	0.263
			(0.250)	(0.621)	(0.250)	(0.641)
OIL_t	-0.0723	0.0590	-0.0915	-0.0599	-0.0928	-0.0703
	(0.0692)	(0.236)	(0.0748)	(0.280)	(0.0748)	(0.279)
OIL_{t-1}			-0.0898	0.0660	-0.0948	0.0780
			(0.0770)	(0.238)	(0.0770)	(0.238)
$SP500_t$	0.136	-0.394	0.148	-0.429	0.151	-0.410
	(0.158)	(0.491)	(0.167)	(0.501)	(0.167)	(0.501)
$SP500_{t-1}$			0.0251	0.360	0.0334	0.335
			(0.161)	(0.544)	(0.161)	(0.540)
BTC_t	0.873***	0.649***	0.865***	0.667***	0.865***	0.673***
	(0.0422)	(0.0953)	(0.0426)	(0.0951)	(0.0428)	(0.0966)
BTC_{t-1}			-0.117***	-0.0455	-0.0868*	0.0220
			(0.0424)	(0.106)	(0.0518)	(0.120)
$MAID_{t-1}$					-0.0348	-0.119
					(0.0340)	(0.0908)
$GOOGLE_t$		0.000274		0.000688		0.000699
		(0.00120)		(0.00121)		(0.00122)
$GOOGLE_{t-1}$				0.00212*		0.00209*
				(0.00117)		(0.00117)
Constant	-0.000898	-0.0104	-0.00120	-0.0217*	-0.00122	-0.0232*
	(0.00180)	(0.0108)	(0.00183)	(0.0118)	(0.00189)	(0.0129)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3414	0.3680	0.3456	0.3940	0.3490	0.3915
DW (original)	2.056629	2.135455	2.049419	2.088052	1.992533	1.949129
DW (transformed)	2.002372	1.982658	1.996713	1.993711	1.993061	1.961913

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 30. Tron regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0884***	0.524***	0.0909***	0.540***	0.0914***	0.541***
	(0.00551)	(0.0458)	(0.00560)	(0.0474)	(0.00559)	(0.0475)
VOLUME$_{t-1}$			0.0127**	-0.0206	-0.0127**	-0.0498
			(0.00562)	(0.0478)	(0.00639)	(0.0679)
GOLD$_t$	0.0821	0.0594	0.0678	0.0886	0.0344	0.0172
	(0.340)	(1.603)	(0.344)	(1.728)	(0.342)	(1.754)
GOLD$_{t-1}$			-0.279	-2.384	-0.244	-2.449
			(0.347)	(1.598)	(0.347)	(1.596)
OIL$_t$	0.00424	-0.219	-0.00484	0.597	-0.0157	0.601
	(0.0914)	(0.600)	(0.103)	(0.769)	(0.104)	(0.774)
OIL$_{t-1}$			-0.0353	-1.337**	-0.0551	-1.353**
			(0.106)	(0.648)	(0.107)	(0.650)
SP500$_t$	0.209	-0.0933	0.261	-0.901	0.298	-0.864
	(0.213)	(1.312)	(0.232)	(1.330)	(0.234)	(1.340)
SP500$_{t-1}$			-0.0380	0.726	-0.108	0.732
			(0.224)	(1.513)	(0.223)	(1.515)
BTC$_t$	1.032***	0.617**	1.022***	0.543*	1.009***	0.552*
	(0.0585)	(0.253)	(0.0598)	(0.276)	(0.0594)	(0.285)
BTC$_{t-1}$			-0.0220	0.241	-0.313***	0.219
			(0.0592)	(0.286)	(0.0676)	(0.296)
TRX$_{t-1}$					0.331***	0.0563
					(0.0320)	(0.0964)
GOOGLE$_t$		0.165***		0.129**		0.125*
		(0.0616)		(0.0639)		(0.0641)
GOOGLE$_{t-1}$				0.0757		0.0665
				(0.0616)		(0.0633)
Constant	-0.0000193	-0.0491**	-0.000871	-0.0500**	-0.00118	-0.0469*
	(0.00285)	(0.0241)	(0.00285)	(0.0240)	(0.00208)	(0.0240)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4309	0.8174	0.4318	0.8310	0.5038	0.8354
DW (original)	1.796946	2.566553	1.821455	2.630186	2.034153	2.095685
DW (transformed)	2.014585	2.036051	2.009969	2.001558	2.049785	2.021066

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 31. BAT regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0255***	0.174***	0.0255***	0.182***	0.0255***	0.181***
	(0.00260)	(0.0249)	(0.00260)	(0.0253)	(0.00261)	(0.0249)
VOLUME$_{t-1}$			0.000689	0.0658**	0.00107	0.115***
			(0.00260)	(0.0254)	(0.00274)	(0.0291)
GOLD$_t$	0.197	0.745	0.225	0.526	0.225	0.448
	(0.246)	(0.625)	(0.247)	(0.702)	(0.247)	(0.692)
GOLD$_{t-1}$			-0.129	0.582	-0.124	0.595
			(0.250)	(0.680)	(0.250)	(0.703)
OIL$_t$	0.0964	0.213	0.112	0.384	0.112	0.474
	(0.0693)	(0.258)	(0.0748)	(0.310)	(0.0748)	(0.312)
OIL$_{t-1}$			0.0411	0.0896	0.0445	0.197
			(0.0771)	(0.262)	(0.0771)	(0.262)
SP500$_t$	0.595***	0.419	0.574***	0.431	0.573***	0.373
	(0.158)	(0.523)	(0.167)	(0.545)	(0.167)	(0.534)
SP500$_{t-1}$			0.129	-0.860	0.138	-0.788
			(0.161)	(0.604)	(0.163)	(0.574)
BTC$_t$	0.803***	0.586***	0.810***	0.616***	0.810***	0.617***
	(0.0422)	(0.104)	(0.0426)	(0.106)	(0.0427)	(0.111)
BTC$_{t-1}$			-0.123***	-0.178	-0.110**	0.0184
			(0.0423)	(0.111)	(0.0505)	(0.122)
BAT$_{t-1}$					-0.0164	-0.293***
					(0.0339)	(0.0930)
GOOGLE$_t$		-0.00262		-0.00489		-0.00549
		(0.0121)		(0.0127)		(0.0125)
GOOGLE$_{t-1}$				-0.00356		-0.00945
				(0.0128)		(0.0125)
Constant	-0.000724	-0.00880	-0.000626	-0.0157	-0.000632	-0.0150
	(0.00178)	(0.0125)	(0.00180)	(0.0142)	(0.00183)	(0.0188)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3808	0.5098	0.3837	0.5204	0.3839	0.5469
DW (original)	2.073656	2.007268	2.073391	1.977529	2.002175	1.929308
DW (transformed)	2.001396	1.984639	2.001437	1.976426	2.000666	1.939553

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 32. Kyber regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00654***	0.0901***	0.00667***	0.0947***	0.00667***	0.0938***
	(0.00137)	(0.0161)	(0.00139)	(0.0171)	(0.00139)	(0.0172)
$VOLUME_{t-1}$			0.00161	0.0128	0.00164	0.0194
			(0.00139)	(0.0171)	(0.00141)	(0.0192)
$GOLD_t$	-0.261	0.915	-0.215	1.447	-0.215	1.422
	(0.284)	(0.786)	(0.286)	(0.910)	(0.286)	(0.912)
$GOLD_{t-1}$			0.0849	1.010	0.0836	1.083
			(0.288)	(0.916)	(0.288)	(0.932)
OIL_t	-0.0154	0.388	0.0136	0.0650	0.0135	0.0596
	(0.0772)	(0.327)	(0.0859)	(0.391)	(0.0860)	(0.393)
OIL_{t-1}			0.0135	-0.0188	0.0134	-0.0362
			(0.0885)	(0.343)	(0.0885)	(0.347)
$SP500_t$	0.403**	-1.110*	0.307	-1.140	0.308	-1.169*
	(0.179)	(0.643)	(0.192)	(0.694)	(0.192)	(0.697)
$SP500_{t-1}$			-0.181	0.522	-0.179	0.417
			(0.186)	(0.760)	(0.187)	(0.764)
BTC_t	0.899***	0.800***	0.890***	0.879***	0.890***	0.891***
	(0.0485)	(0.126)	(0.0491)	(0.135)	(0.0492)	(0.139)
BTC_{t-1}			-0.128***	0.133	-0.125**	0.217
			(0.0487)	(0.137)	(0.0575)	(0.155)
$KYBER_{t-1}$					-0.00325	-0.0894
					(0.0339)	(0.0951)
$GOOGLE_t$		0.0000118		0.000220		0.000159
		(0.00133)		(0.00144)		(0.00145)
$GOOGLE_{t-1}$				-0.000608		-0.000643
				(0.00140)		(0.00141)
	-0.000495	-0.0114	-0.000723	-0.0232	-0.000727	-0.0239
Constant	(0.00229)	(0.0184)	(0.00233)	(0.0214)	(0.00234)	(0.0234)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3115	0.3841	0.3165	0.3817	0.3161	0.3901
DW (original)	1.870073	1.770098	1.857616	1.762428	1.977099	1.975933
DW (transformed)	1.989671	1.988167	1.988597	1.989057	1.988138	1.990511

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 33. Dogecoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0394***	0.0685***	0.0411***	0.0701***	0.0411***	0.0704***
	(0.00272)	(0.00756)	(0.00269)	(0.00765)	(0.00268)	(0.00766)
$VOLUME_{t-1}$			0.0161***	0.0209***	0.0102***	0.00768
			(0.00268)	(0.00775)	(0.00302)	(0.0102)
$GOLD_t$	0.200	0.368	0.215	0.196	0.203	0.195
	(0.213)	(0.660)	(0.210)	(0.753)	(0.209)	(0.762)
$GOLD_{t-1}$			-0.0818	0.323	-0.108	0.126
			(0.212)	(0.741)	(0.212)	(0.725)
OIL_t	0.0615	0.0761	0.0562	0.218	0.0544	0.220
	(0.0581)	(0.284)	(0.0632)	(0.332)	(0.0632)	(0.340)
OIL_{t-1}			0.00876	-0.0105	-0.00287	-0.0570
			(0.0652)	(0.284)	(0.0653)	(0.286)
$SP500_t$	0.280**	-0.0368	0.300**	-0.307	0.300**	-0.311
	(0.134)	(0.561)	(0.142)	(0.590)	(0.142)	(0.595)
$SP500_{t-1}$			0.162	-0.640	0.0955	-0.535
			(0.137)	(0.641)	(0.137)	(0.656)
BTC_t	0.778***	0.856***	0.771***	0.917***	0.768***	0.902***
	(0.0364)	(0.111)	(0.0362)	(0.116)	(0.0361)	(0.114)
BTC_{t-1}			-0.0861**	0.0795	-0.222***	-0.0811
			(0.0359)	(0.120)	(0.0436)	(0.140)
$DOGE_{t-1}$					0.181***	0.189**
					(0.0326)	(0.0908)
$GOOGLE_t$		0.0272**		0.0217		0.0221
		(0.0137)		(0.0148)		(0.0150)
$GOOGLE_{t-1}$				-0.00443		-0.00958
				(0.0150)		(0.0155)
Constant	-0.00140	-0.00687	-0.00273*	-0.0106	-0.00257*	-0.00936
	(0.00166)	(0.0151)	(0.00160)	(0.0162)	(0.00137)	(0.0138)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4600	0.5989	0.4823	0.6092	0.5099	0.6301
DW (original)	1.918313	1.845841	1.973502	1.841116	2.050942	2.005490
DW (transformed)	1.998641	2.006171	1.999050	2.001713	2.022269	2.006630

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 34. Salt regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00198***	0.0280**	0.00196***	0.0253**	0.00194***	0.0236**
	(0.000597)	(0.0110)	(0.000597)	(0.0110)	(0.000594)	(0.0109)
$VOLUME_{t-1}$			0.000121	0.00601	-0.000322	0.0138
			(0.000597)	(0.0109)	(0.000598)	(0.0109)
$GOLD_t$	0.00206	0.121	0.0421	-0.0114	0.0138	-0.547
	(0.327)	(0.953)	(0.329)	(1.055)	(0.328)	(1.036)
$GOLD_{t-1}$			-0.0456	0.891	0.0169	0.614
			(0.332)	(1.007)	(0.332)	(1.044)
OIL_t	-0.0976	-0.241	-0.0798	-0.291	-0.0883	-0.181
	(0.0911)	(0.383)	(0.0990)	(0.462)	(0.0990)	(0.451)
OIL_{t-1}			-0.0465	0.388	-0.0541	0.220
			(0.102)	(0.396)	(0.102)	(0.398)
$SP500_t$	0.359*	-0.751	0.297	-0.559	0.350	-0.401
	(0.208)	(0.797)	(0.222)	(0.822)	(0.223)	(0.793)
$SP500_{t-1}$			-0.406*	-0.788	-0.507**	-1.032
			(0.214)	(0.911)	(0.213)	(0.848)
BTC_t	0.979***	1.004***	0.975***	1.082***	0.962***	1.125***
	(0.0559)	(0.150)	(0.0564)	(0.152)	(0.0562)	(0.156)
BTC_{t-1}			-0.0706	-0.145	-0.288***	0.201
			(0.0560)	(0.159)	(0.0643)	(0.184)
$SALT_{t-1}$					0.253***	-0.371***
					(0.0328)	(0.0836)
$GOOGLE_t$		0.0104		0.0128		0.00885
		(0.00984)		(0.0102)		(0.00977)
$GOOGLE_{t-1}$				0.00459		-0.00456
				(0.0101)		(0.00988)
Constant	-0.00238	-0.0272	-0.00246	-0.0358*	-0.00197	-0.0330
	(0.00241)	(0.0183)	(0.00241)	(0.0215)	(0.00194)	(0.0304)
Observations	878	126	877	125	877	125
Adj. R-squared	0.2760	0.2692	0.2775	0.2788	0.3095	0.4151
DW (original)	2.018836	2.160320	2.024539	2.112832	1.998854	1.898032
DW (transformed)	1.993342	1.926981	1.991649	1.964554	1.998294	1.935153

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 35. Verge regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0266***	0.189***	0.0264***	0.190***	0.0263***	0.189***
	(0.00220)	(0.0156)	(0.00222)	(0.00862)	(0.00221)	(0.00856)
$VOLUME_{t-1}$			-0.00231	0.135***	0.00155	0.147***
			(0.00222)	(0.00946)	(0.00239)	(0.0114)
$GOLD_t$	0.0622	1.892	0.0908	-0.180	0.0682	0.0738
	(0.354)	(1.523)	(0.357)	(0.889)	(0.357)	(0.899)
$GOLD_{t-1}$			-0.236	0.130	-0.284	0.259
			(0.360)	(0.883)	(0.358)	(0.884)
OIL_t	-0.0213	-0.119	0.00264	-0.473	0.000270	-0.415
	(0.0949)	(0.582)	(0.107)	(0.387)	(0.106)	(0.386)
OIL_{t-1}			0.0388	-0.538	0.0374	-0.585*
			(0.110)	(0.335)	(0.108)	(0.333)
$SP500_t$	0.193	-0.202	0.192	-0.00241	0.205	-0.0729
	(0.221)	(1.251)	(0.240)	(0.695)	(0.237)	(0.691)
$SP500_{t-1}$			0.102	0.131	0.140	0.167
			(0.233)	(0.767)	(0.231)	(0.757)
BTC_t	1.068***	0.244	1.050***	0.927***	1.049***	0.904***
	(0.0605)	(0.235)	(0.0615)	(0.139)	(0.0616)	(0.140)
BTC_{t-1}			-0.162***	-0.213	0.0209	-0.195
			(0.0610)	(0.144)	(0.0709)	(0.144)
XVG_{t-1}					-0.167***	-0.0819*
					(0.0335)	(0.0488)
$GOOGLE_t$		0.253***		0.0458		0.0517*
		(0.0473)		(0.0283)		(0.0282)
$GOOGLE_{t-1}$				0.00310		0.0237
				(0.0260)		(0.0285)
Constant	-0.00348	-0.0633***	-0.00284	-0.0892***	-0.00327	-0.0938***
	(0.00300)	(0.0239)	(0.00305)	(0.0183)	(0.00371)	(0.0192)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3594	0.7883	0.3632	0.9157	0.3981	0.9143
DW (original)	1.784818	2.215832	1.776200	1.826652	1.997737	1.758672
DW (transformed)	2.007217	2.041104	2.009997	1.941579	2.024994	1.916840

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 36. Bitcoin Gold regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0417***	0.190***	0.0421***	0.192***	0.0421***	0.182***
	(0.00319)	(0.0133)	(0.00318)	(0.0148)	(0.00321)	(0.0155)
$VOLUME_{t-1}$			0.00695**	-0.0275**	0.00888**	0.0607***
			(0.00318)	(0.0138)	(0.00350)	(0.0227)
$GOLD_t$	-0.246	0.131	-0.205	0.0421	-0.201	0.174
	(0.334)	(0.597)	(0.334)	(0.658)	(0.335)	(0.661)
$GOLD_{t-1}$			-0.294	0.670	-0.302	0.680
			(0.337)	(0.610)	(0.337)	(0.639)
OIL_t	-0.000248	-0.258	-0.0104	-0.365	-0.00933	-0.413
	(0.0919)	(0.221)	(0.100)	(0.286)	(0.100)	(0.282)
OIL_{t-1}			-0.0570	0.129	-0.0544	-0.0269
			(0.103)	(0.239)	(0.103)	(0.241)
$SP500_t$	0.304	0.0978	0.321	0.177	0.319	0.113
	(0.211)	(0.482)	(0.225)	(0.502)	(0.225)	(0.506)
$SP500_{t-1}$			-0.0621	-0.329	-0.0497	-0.0264
			(0.217)	(0.566)	(0.217)	(0.552)
BTC_t	0.855***	0.658***	0.848***	0.678***	0.847***	0.711***
	(0.0569)	(0.0894)	(0.0573)	(0.0948)	(0.0576)	(0.0959)
BTC_{t-1}			-0.117**	0.0604	-0.0807	0.324***
			(0.0569)	(0.100)	(0.0640)	(0.121)
BTG_{t-1}					-0.0452	-0.394***
					(0.0341)	(0.0879)
$GOOGLE_t$		-0.000255		-0.000784		-0.00100
		(0.00239)		(0.00244)		(0.00245)
$GOOGLE_{t-1}$				0.00262		0.00123
				(0.00243)		(0.00242)
Constant	-0.00470*	-0.0389***	-0.00543**	-0.0409***	-0.00564**	-0.0568***
	(0.00253)	(0.00991)	(0.00256)	(0.0113)	(0.00268)	(0.0154)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3303	0.7163	0.3346	0.7052	0.3363	0.7212
DW (original)	1.965843	2.465738	1.960350	2.322298	1.987806	1.798893
DW (transformed)	1.995439	1.955246	1.998138	1.876188	1.994267	1.832116

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 37. Icon regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	-0.000226***	0.00114***	-0.000232***	0.00116***	-0.000242***	0.00113***
	(0.0000764)	(0.000268)	(0.0000762)	(0.000279)	(0.00007.62)	(0.000284)
$VOLUME_{t-1}$			0.0000653	0.0000200	-0.0000294	-0.000100
			(0.0000764)	(0.000285)	(0.0000765)	(0.000304)
$GOLD_t$	-0.139	0.753	-0.0918	1.391	-0.0457	1.099
	(0.327)	(0.748)	(0.328)	(0.924)	(0.329)	(0.915)
$GOLD_{t-1}$			-0.110	1.011	-0.0910	0.980
			(0.332)	(0.902)	(0.330)	(0.844)
OIL_t	0.128	0.248	0.135	0.185	0.132	0.235
	(0.0928)	(0.335)	(0.0991)	(0.401)	(0.0976)	(0.400)
OIL_{t-1}			0.0253	-0.251	0.0584	-0.292
			(0.102)	(0.341)	(0.100)	(0.337)
$SP500_t$	0.207	-0.370	0.193	-0.575	0.193	-0.682
	(0.210)	(0.652)	(0.222)	(0.725)	(0.219)	(0.718)
$SP500_{t-1}$			0.224	0.183	0.255	0.0142
			(0.214)	(0.772)	(0.213)	(0.793)
BTC_t	1.000***	1.217***	1.014***	1.220***	1.004***	1.205***
	(0.0559)	(0.130)	(0.0564)	(0.139)	(0.0565)	(0.135)
BTC_{t-1}			-0.168***	-0.0572	0.0874	-0.451**
			(0.0560)	(0.147)	(0.0654)	(0.173)
ICX_{t-1}					-0.275***	0.408***
					(0.0325)	(0.0869)
$GOOGLE_t$		0.00797		0.0176		0.0173
		(0.0137)		(0.0157)		(0.0155)
$GOOGLE_{t-1}$				0.0194		0.0162
				(0.0156)		(0.0156)
Constant	0.000919	-0.00622	0.000862	-0.0205	0.00124	-0.0173
	(0.00229)	(0.0197)	(0.00229)	(0.0207)	(0.00310)	(0.0140)
Observations	878	126	877	125	877	125
Adj. R-squared	0.2809	0.4271	0.2860	0.4036	0.3475	0.5109
DW (original)	2.120112	1.641863	2.119225	1.707923	1.986907	2.047089
DW (transformed)	1.989210	1.982143	1.986694	1.936542	2.007540	2.007199

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 38. Chainlink regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0491***	0.0988***	0.0490***	0.0962***	0.0490***	0.0966***
	(0.00283)	(0.0154)	(0.00284)	(0.0159)	(0.00284)	(0.0160)
$VOLUME_{t-1}$			0.000874	-0.00884	0.00973***	0.0256
			(0.00283)	(0.0159)	(0.00326)	(0.0182)
$GOLD_t$	0.154	0.879	0.224	1.002	0.247	0.665
	(0.280)	(0.783)	(0.282)	(0.892)	(0.284)	(0.857)
$GOLD_{t-1}$			-0.135	1.078	-0.0945	0.645
			(0.286)	(0.858)	(0.285)	(0.883)
OIL_t	0.0436	0.124	0.0180	0.101	0.0210	0.0434
	(0.0804)	(0.322)	(0.0853)	(0.390)	(0.0849)	(0.380)
OIL_{t-1}			-0.117	0.187	-0.1000	0.249
			(0.0880)	(0.332)	(0.0873)	(0.332)
$SP500_t$	0.601***	0.697	0.665***	0.417	0.652***	0.743
	(0.181)	(0.661)	(0.192)	(0.703)	(0.190)	(0.670)
$SP500_{t-1}$			0.0215	-0.730	0.110	-0.0958
			(0.184)	(0.766)	(0.185)	(0.710)
BTC_t	0.770***	0.912***	0.771***	0.936***	0.769***	0.964***
	(0.0479)	(0.129)	(0.0486)	(0.134)	(0.0487)	(0.138)
BTC_{t-1}			-0.1000**	0.149	0.0523	0.508***
			(0.0483)	(0.141)	(0.0548)	(0.154)
$LINK_{t-1}$					-0.203***	-0.417***
					(0.0334)	(0.0865)
$GOOGLE_t$		-0.00160		-0.000649		0.00149
		(0.00703)		(0.00731)		(0.00705)
$GOOGLE_{t-1}$				0.00438		0.00746
				(0.00730)		(0.00712)
Constant		0.0155		0.0115		0.0158
		(0.0157)		(0.0181)		(0.0281)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4171	0.5032	0.4182	0.4950	0.4297	0.5680
DW (original)	2.188818	2.074042	2.187085	2.030622	1.993238	1.952182
DW (transformed)	1.995911	1.982705	1.993707	1.947952	1.999078	1.976528

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 39. Decred regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00355***	0.00869*	0.00361***	0.00921**	0.00361***	0.00917*
	(0.000606)	(0.00441)	(0.000606)	(0.00450)	(0.000606)	(0.00464)
$VOLUME_{t-1}$			-0.000533	-0.00273	-0.000506	-0.00202
			(0.000606)	(0.00448)	(0.000618)	(0.00457)
$GOLD_t$	0.0921	0.219	0.103	0.330	0.103	0.341
	(0.202)	(0.546)	(0.203)	(0.604)	(0.203)	(0.602)
$GOLD_{t-1}$			-0.0721	-0.129	-0.0703	-0.263
			(0.205)	(0.576)	(0.205)	(0.599)
OIL_t	-0.0634	0.253	-0.0718	0.0395	-0.0720	0.0356
	(0.0566)	(0.220)	(0.0612)	(0.272)	(0.0613)	(0.270)
OIL_{t-1}			0.0162	0.0669	0.0151	0.0677
			(0.0631)	(0.229)	(0.0632)	(0.231)
$SP500_t$	0.267**	-0.0104	0.296**	-0.0432	0.297**	-0.00606
	(0.129)	(0.457)	(0.137)	(0.480)	(0.137)	(0.478)
$SP500_{t-1}$			0.299**	0.321	0.301**	0.469
			(0.132)	(0.526)	(0.132)	(0.512)
BTC_t	0.889***	0.785***	0.893***	0.780***	0.893***	0.774***
	(0.0345)	(0.0869)	(0.0349)	(0.0902)	(0.0349)	(0.0941)
BTC_{t-1}			-0.0701**	0.153	-0.0641	0.368***
			(0.0346)	(0.0931)	(0.0459)	(0.117)
$DECRED_{t-1}$					-0.00667	-0.278***
					(0.0339)	(0.0927)
$GOOGLE_t$		0.000748		0.000485		0.000485
		(0.000980)		(0.00101)		(0.00102)
$GOOGLE_{t-1}$				-0.000885		-0.000220
				(0.000998)		(0.000995)
Constant	-0.00100	-0.00825	-0.000828	-0.00429	-0.000837	-0.00818
	(0.00147)	(0.0107)	(0.00148)	(0.0126)	(0.00149)	(0.0158)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4556	0.4446	0.4579	0.4463	0.4577	0.4451
DW (original)	2.051440	2.228189	2.053772	2.221858	2.007712	1.983916
DW (transformed)	2.004770	1.979010	2.004782	2.003291	2.003366	1.982906

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40. Komodo regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0119***	0.0985***	0.0124***	0.105***	0.0124***	0.105***
	(0.00142)	(0.0180)	(0.00146)	(0.0190)	(0.00146)	(0.0191)
$VOLUME_{t-1}$			0.00116	0.0331*	0.00136	0.0224
			(0.00145)	(0.0185)	(0.00151)	(0.0209)
$GOLD_t$	-0.383	0.0541	-0.291	0.124	-0.286	0.105
	(0.242)	(0.723)	(0.244)	(0.852)	(0.245)	(0.861)
$GOLD_{t-1}$			0.167	0.197	0.166	0.132
			(0.247)	(0.839)	(0.247)	(0.829)
OIL_t	-0.00253	0.0520	-0.0211	-0.0187	-0.0202	-0.0404
	(0.0647)	(0.316)	(0.0733)	(0.373)	(0.0732)	(0.379)
OIL_{t-1}			-0.0772	-0.179	-0.0766	-0.195
			(0.0754)	(0.320)	(0.0753)	(0.320)
$SP500_t$	0.597***	0.469	0.576***	0.334	0.574***	0.319
	(0.151)	(0.618)	(0.164)	(0.670)	(0.164)	(0.675)
$SP500_{t-1}$			-0.0880	0.0754	-0.0807	0.0538
			(0.159)	(0.726)	(0.160)	(0.739)
BTC_t	0.917***	0.578***	0.889***	0.556***	0.889***	0.569***
	(0.0414)	(0.123)	(0.0421)	(0.128)	(0.0424)	(0.130)
BTC_{t-1}			-0.133***	0.0555	-0.116**	0.0182
			(0.0418)	(0.133)	(0.0517)	(0.141)
$KOMODO_{t-1}$					-0.0197	0.122
					(0.0340)	(0.0954)
$GOOGLE_t$		-0.000889		0.000337		0.000304
		(0.00276)		(0.00299)		(0.00300)
$GOOGLE_{t-1}$				0.00208		0.00198
				(0.00294)		(0.00294)
Constant	-0.00284	-0.0174	-0.00327	-0.0310	-0.00332	-0.0291
	(0.00208)	(0.0179)	(0.00210)	(0.0200)	(0.00215)	(0.0185)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4263	0.3310	0.4317	0.3222	0.4345	0.3316
DW (original)	1.767709	1.746790	1.761786	1.802797	1.986387	1.986390
DW (transformed)	1.996298	1.924216	1.991528	1.949015	1.989470	1.988421

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41. Ark regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.0113***	0.0289***	0.0113***	0.0290***	0.0113***	0.0288***
	(0.00107)	(0.00679)	(0.00107)	(0.00685)	(0.00107)	(0.00687)
$VOLUME_{t-1}$			0.000852	0.00410	0.00115	0.00881
			(0.00107)	(0.00694)	(0.00114)	(0.00739)
$GOLD_t$	0.0648	1.037*	0.112	0.514	0.113	0.505
	(0.253)	(0.598)	(0.254)	(0.685)	(0.255)	(0.684)
$GOLD_{t-1}$			0.150	-0.559	0.172	-0.504
			(0.257)	(0.653)	(0.257)	(0.678)
OIL_t	0.0872	0.162	0.0822	0.345	0.0825	0.353
	(0.0712)	(0.245)	(0.0768)	(0.297)	(0.0769)	(0.299)
OIL_{t-1}			-0.0667	-0.165	-0.0634	-0.131
			(0.0792)	(0.250)	(0.0792)	(0.251)
$SP500_t$	0.533***	-0.257	0.531***	-0.325	0.529***	-0.288
	(0.162)	(0.502)	(0.172)	(0.528)	(0.172)	(0.528)
$SP500_{t-1}$			-0.0559	-0.384	-0.0415	-0.363
			(0.166)	(0.582)	(0.167)	(0.574)
BTC_t	0.859***	0.792***	0.854***	0.803***	0.854***	0.803***
	(0.0433)	(0.0957)	(0.0438)	(0.0985)	(0.0439)	(0.101)
BTC_{t-1}			-0.102**	0.000662	-0.0769	0.103
			(0.0434)	(0.101)	(0.0524)	(0.124)
ARK_{t-1}					-0.0295	-0.161*
					(0.0340)	(0.0932)
$GOOGLE_t$		-0.00664		-0.00516		-0.00534
		(0.00545)		(0.00567)		(0.00564)
$GOOGLE_{t-1}$				-0.00204		-0.00306
				(0.00558)		(0.00561)
Constant		-0.0165		-0.0164		-0.0183
		(0.0120)		(0.0132)		(0.0154)
Observations	878	126	877	125	877	125
Adj. R-squared	0.3923	0.4330	0.3942	0.4323	0.3962	0.4467
DW (original)	2.073841	2.028056	2.067813	2.028635	1.992786	1.966223
DW (transformed)	2.000231	1.969282	1.994698	1.983344	1.992104	1.975845

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 42. PIVX regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00231***	0.0293***	0.00221***	0.0297***	0.00221***	0.0296***
	(0.000467)	(0.00763)	(0.000461)	(0.00784)	(0.000462)	(0.00788)
$VOLUME_{t-1}$			0.00157***	-0.00327	0.00175***	-0.00426
			(0.000461)	(0.00780)	(0.000467)	(0.00833)
$GOLD_t$	-0.248	0.561	-0.193	0.728	-0.189	0.723
	(0.270)	(0.719)	(0.268)	(0.828)	(0.268)	(0.834)
$GOLD_{t-1}$			-0.314	0.510	-0.317	0.500
			(0.271)	(0.801)	(0.271)	(0.804)
OIL_t	0.0581	-0.152	0.0345	-0.329	0.0325	-0.323
	(0.0761)	(0.297)	(0.0809)	(0.360)	(0.0808)	(0.364)
OIL_{t-1}			-0.0772	-0.0789	-0.0752	-0.0598
			(0.0834)	(0.303)	(0.0833)	(0.305)
$SP500_t$	0.354**	-0.226	0.424**	-0.384	0.427**	-0.391
	(0.173)	(0.599)	(0.181)	(0.641)	(0.181)	(0.644)
$SP500_{t-1}$			0.115	0.0732	0.157	0.0430
			(0.175)	(0.700)	(0.175)	(0.707)
BTC_t	0.832***	0.807***	0.835***	0.825***	0.833***	0.822***
	(0.0461)	(0.115)	(0.0460)	(0.122)	(0.0463)	(0.122)
BTC_{t-1}			-0.144***	0.192	-0.0930*	0.166
			(0.0458)	(0.126)	(0.0538)	(0.145)
$PIVX_{t-1}$					-0.0623*	0.0373
					(0.0336)	(0.0943)
$GOOGLE_t$		-0.00145		-0.000560		-0.000560
		(0.00207)		(0.00220)		(0.00221)
$GOOGLE_{t-1}$				0.00130		0.00140
				(0.00219)		(0.00221)
Constant	-0.00226	-0.0212	-0.00317	-0.0310*	-0.00334	-0.0302*
	(0.00193)	(0.0155)	(0.00195)	(0.0182)	(0.00206)	(0.0179)
Observations	878	126	877	125	877	125
Adj. R-squared	0.2981	0.3294	0.3154	0.3240	0.3243	0.3195
DW (original)	2.085677	1.967738	2.074384	1.970470	1.992348	1.999037
DW (transformed)	2.002490	1.984493	2.005214	1.985003	1.996502	1.993329

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 43. Vertcoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00799***	0.0337***	0.00806***	0.0335***	0.00806***	0.0331***
	(0.000434)	(0.00509)	(0.000428)	(0.00519)	(0.000428)	(0.00520)
$VOLUME_{t-1}$			-0.00248***	0.00542	-0.00246***	0.0177***
			(0.000428)	(0.00515)	(0.000505)	(0.00576)
$GOLD_t$	-0.341	0.276	-0.355	0.0226	-0.355	0.0707
	(0.289)	(0.581)	(0.286)	(0.628)	(0.286)	(0.623)
$GOLD_{t-1}$			0.153	0.392	0.153	0.157
			(0.289)	(0.595)	(0.290)	(0.624)
OIL_t	-0.0122	0.0468	-0.0373	0.299	-0.0373	0.315
	(0.0820)	(0.222)	(0.0865)	(0.281)	(0.0867)	(0.277)
OIL_{t-1}			-0.0552	-0.191	-0.0551	-0.256
			(0.0892)	(0.237)	(0.0893)	(0.236)
$SP500_t$	0.188	0.147	0.215	0.00585	0.215	-0.0183
	(0.186)	(0.476)	(0.194)	(0.492)	(0.194)	(0.489)
$SP500_{t-1}$			0.190	-0.534	0.190	-0.245
			(0.186)	(0.548)	(0.187)	(0.528)
BTC_t	0.897***	0.785***	0.903***	0.820***	0.903***	0.817***
	(0.0495)	(0.0880)	(0.0492)	(0.0914)	(0.0493)	(0.0942)
BTC_{t-1}			-0.0167	-0.0507	-0.0147	0.217*
			(0.0489)	(0.0949)	(0.0576)	(0.116)
$VERT_{t-1}$					-0.00217	-0.366***
					(0.0334)	(0.0859)
$GOOGLE_t$		0.00736*		0.00808**		0.00809**
		(0.00385)		(0.00387)		(0.00388)
$GOOGLE_{t-1}$				0.00443		0.00693*
				(0.00388)		(0.00385)
Constant	-0.00487**	-0.0361***	-0.00362*	-0.0450***	-0.00363*	-0.0575***
	(0.00204)	(0.0101)	(0.00201)	(0.0114)	(0.00202)	(0.0154)
Observations	878	126	877	125	877	125
Adj. R-squared	0.4369	0.5503	0.4556	0.5548	0.4551	0.5398
DW (original)	2.107871	2.440205	2.130250	2.429411	2.031821	1.951381
DW (transformed)	2.009955	1.953632	2.013060	2.001520	2.012645	1.993889

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 44. MonaCoin regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VOLUME$_t$	0.0155***	0.0340***	0.0154***	0.0334***	0.0154***	0.0336***
	(0.000604)	(0.00223)	(0.000602)	(0.00221)	(0.000602)	(0.00221)
VOLUME$_{t-1}$			0.000779	-0.00143	0.000902	0.00526
			(0.000602)	(0.00227)	(0.000799)	(0.00393)
GOLD$_t$	0.0588	-0.634	0.144	-0.598	0.145	-0.555
	(0.294)	(0.627)	(0.295)	(0.723)	(0.295)	(0.719)
GOLD$_{t-1}$			0.203	-0.539	0.203	-0.676
			(0.298)	(0.674)	(0.298)	(0.691)
OIL$_t$	-0.0305	-0.182	-0.0998	-0.250	-0.0994	-0.288
	(0.0823)	(0.265)	(0.0891)	(0.309)	(0.0892)	(0.309)
OIL$_{t-1}$			-0.237***	-0.346	-0.237**	-0.450*
			(0.0918)	(0.266)	(0.0919)	(0.269)
SP500$_t$	0.138	-0.0511	0.231	-0.271	0.230	-0.250
	(0.188)	(0.530)	(0.200)	(0.556)	(0.200)	(0.554)
SP500$_{t-1}$			-0.108	0.309	-0.108	0.461
			(0.192)	(0.595)	(0.192)	(0.582)
BTC$_t$	0.780***	0.980***	0.761***	0.989***	0.761***	0.998***
	(0.0504)	(0.102)	(0.0508)	(0.103)	(0.0510)	(0.109)
BTC$_{t-1}$			-0.0641	0.232**	-0.0586	0.378***
			(0.0504)	(0.106)	(0.0570)	(0.137)
MONA$_{t-1}$					-0.00784	-0.180*
					(0.0339)	(0.0928)
GOOGLE$_t$		0.000142		0.00112		0.00138
		(0.00262)		(0.00265)		(0.00266)
GOOGLE$_{t-1}$				0.00209		0.00230
				(0.00270)		(0.00270)
Constant	-0.00553**	-0.0206	-0.00613***	-0.0289*	-0.00617***	-0.0349**
	(0.00217)	(0.0133)	(0.00219)	(0.0148)	(0.00221)	(0.0176)
Observations	878	126	877	125	877	125
Adj. R-squared	0.5198	0.7370	0.5231	0.7502	0.5225	0.7575
DW (original)	2.032818	1.954103	2.030753	1.933423	2.001297	1.921892
DW (transformed)	2.002771	1.957923	2.000945	1.981477	1.999700	1.948460

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 45. Factom regression results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$VOLUME_t$	0.00229	0.0452***	0.00206	0.0456***	0.00207	0.0447***
	(0.00171)	(0.00809)	(0.00171)	(0.00828)	(0.00171)	(0.00835)
$VOLUME_{t-1}$			-0.00117	0.0106	-0.00144	-0.00290
			(0.00171)	(0.00831)	(0.00171)	(0.00924)
$GOLD_t$	0.359	0.507	0.436	0.518	0.439	0.288
	(0.316)	(0.777)	(0.317)	(0.893)	(0.317)	(0.890)
$GOLD_{t-1}$			-0.137	0.396	-0.184	0.128
			(0.321)	(0.869)	(0.321)	(0.836)
OIL_t	-0.0261	0.207	-0.0178	0.310	-0.0166	0.343
	(0.0902)	(0.329)	(0.0956)	(0.394)	(0.0959)	(0.401)
OIL_{t-1}			-0.0216	-0.283	-0.0236	-0.362
			(0.0987)	(0.333)	(0.0989)	(0.335)
$SP500_t$	0.294	-0.286	0.278	-0.208	0.285	-0.211
	(0.204)	(0.658)	(0.215)	(0.697)	(0.215)	(0.689)
$SP500_{t-1}$			0.0807	0.203	0.0423	0.0877
			(0.206)	(0.764)	(0.206)	(0.795)
BTC_t	0.762***	0.634***	0.777***	0.709***	0.777***	0.662***
	(0.0541)	(0.130)	(0.0545)	(0.135)	(0.0547)	(0.132)
BTC_{t-1}			-0.206***	-0.146	-0.264***	-0.284*
			(0.0542)	(0.141)	(0.0599)	(0.144)
$FACTOM_{t-1}$					0.0775**	0.326***
					(0.0338)	(0.0886)
$GOOGLE_t$		0.000313		0.000334		0.0000464
		(0.00122)		(0.00128)		(0.00126)
$GOOGLE_{t-1}$				-0.00151		-0.00185
				(0.00126)		(0.00125)
Constant	-0.000769	-0.0175	-0.000180	-0.0152	-0.000104	-0.00458
	(0.00224)	(0.0183)	(0.00230)	(0.0218)	(0.00216)	(0.0176)
Observations	878	126	877	125	877	125
Adj. R-squared	0.1981	0.2936	0.2080	0.2974	0.2037	0.3556
DW (original)	2.153590	1.903334	2.157196	1.931994	2.002874	2.025823
DW (transformed)	1.997975	1.989230	1.993932	2.002596	2.000049	1.983122

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$