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Predictive Modelling of the Bitcoin Price: A Comprehensive Analysis of Time Series Models

The usage of time-based models in predicting the price of Bitcoin in both the short and long term future

Ana Rita Pires da Costa

Project Work

presented as partial requirement for obtaining the Master Degree Program in Information Management

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Instituto Superior de Estatística e Gestão de Informação
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PREDICTIVE MODELLING OF THE BITCOIN PRICE: A COMPREHENSIVE ANALYSIS OF TIME SERIES MODELS

By

Ana Rita Pires da Costa

Project Work presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Ana Rita Pires da Costa

Lisbon, 27th of November of 2023

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ABSTRACT

The extraordinary volatility of Bitcoin is attributed to a multitude of external factors that are difficult to identify and monitor for predictive modeling. The impact of the Bitcoin halving introduces still another level of complexity, implying possible stability in the far future, subject to discernible seasonality indicators. This thesis aims to identify what variables influence the value of bitcoin and what kind of models better forecast its price. Following the CRISP-DM methodology, data was collected from online sources, analyzed, and treated accordingly as means to be fed to different types of models: Autoregressive Integrated Moving Average (ARIMA), Vector Autoregressive (VAR), Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) Layers and Prophet. The variables that were found to have the greatest potential for inclusion in prediction models were Bitcoin volume, the VT index, and currencies like the Israeli New Shekel and Euro, as well as silver and copper. Although Prophet showed potential, it was clear that it had limitations, especially when it came to predicting long-term outcomes with variables other than Bitcoin. Furthermore, in these models, regressors appeared to be a promising technique, but could only be used to anticipate known futures. While the RNN model with LSTM layers seemed reliable for short-term forecasts, it was not practical for making large-scale, long-term investment decisions. These results highlight how difficult it is currently to develop predictive models that accurately predict Bitcoin values, particularly for large-scale, long-term decision-making in the investment market.

KEYWORDS

Time series forecasting; Price Prediction; ARIMA; VAR; RNN; LSTM Layers; Prophet

Sustainable Development Goals (SGD):

8 DECENT WORK AND ECONOMIC GROWTH

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

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LIST OF ABBREVIATIONS AND ACRONYMS

ANN Artificial Neural Network

ARIMA Autoregressive Integrated Moving Average

Bi-LSTM Bidirectional Long Short-Term Memory

CNN Convolutional Neural Network

GRU Gated Recurrent Unit

LSTM Long Short-Term Memory

LSTM-NP Long Short-Term Memory with a Neural Prophet

ML Machine Learning

NN Neural Networks

PoC Proof of Concept

RNN Recurrent Neural Network

SANN Stacked Artificial Neural Network

SVM Support Vector Machine

VAR Vector Autoregressive

VOO Vanguard 500 Index Fund

VT Vanguard Total World Stock Index Fund

1. INTRODUCTION

Having gained significant influence, virtual currencies are now recognized as a key factor in both the financial market and business opportunities. With respect to the latter, they have proved to be valuable when it comes to international trade, mainly in times of emergency when a quick response is required (DeVries, 2016).

Bitcoin is the first ever created cryptocurrency (Pintelas et al., 2020), though nowadays there are numerous, many other cryptocurrencies apart from it. Some examples include Ethereum, Binance Coin, Cardano, Polygon, and others. However, Bitcoin stands as one of the most popular in that ecosystem (Pintelas et al., 2020).

The perception of security provided by the Bitcoin blockchain technology encourages individuals to use it. On top of that, the economic background they are facing makes users bolder in that same aspect. Even so, value fluctuations play a major role in undermining their trust (Hamayel & Owda, 2021). In addition, a period of stabilization has been noticed by investors, though they are aware there is little to no guarantee of immediate returns on investment (Kozlovskyi et al., 2022). Theoretically speaking, the issue would be minimized with growth in Bitcoin's capacity and its adoption in day to day transactions, however, cryptocurrencies as a whole are very much still in their infancy (DeVries, 2016). In this sense, cryptocurrency price prediction can provide some support and guidance in the decision-making process of users (Pintelas et al., 2020).

Given its inherent nature, Bitcoin is challenging to predict. It is not only extremely volatile, but also highly flexible (Hamayel & Owda, 2021; Mensi et al., 2019; Pintelas et al., 2020), as it is susceptible to a wide range of factors ('Analysis on Crypto-Currency', 2017; Catania & Sandholdt, 2019; Kaplan et al., n.d.), some of which hard to capture in data. The Bitcoin price curve has shown various ups and downs (Caporale et al., 2019). Additionally, every four years it goes through the halving event, which can be translated into a planned reduction in the rate at which new bitcoins are created and introduced into circulation, used as a control measure (Antonopoulos, 2015). This complex dynamic, makes it a fascinating yet hard subject to research.

The main purpose of this project is to test the possibility of forecasting the price of Bitcoin using different the time series models, as means to address the problem mentioned above. This was done using CRISP-DM methodology, along with an iterative development approach. It was developed under the guidance of the Lab department of agap2IT, which specializes in research and innovation in areas including AI, Advanced Analytics and Blockchain.

2. LITERATURE REVIEW

The concept of money has existed for a very long time. However, it never remained static. This is due to accompanying society as it undergoes changes in different fields. In this context, people first started to use currencies of physical nature, as means of exchange for goods and services (Davies, 2010).

Globally speaking, the fiat currency is the most usually used currency in day-to-day transactions ('Analysis on Crypto-Currency', 2017). It is issued and regulated by a central authority or a central bank while holding no intrinsic value. This is due to not being backed by any physical commodity, such as gold. Instead, the worth is determined by its recognition and acceptance as a reliable or better in fact legal tender (Bartos, 2015; DeVries, 2016; Yermack, n.d.).

Thanks to technological advancements, currencies began to be supported in non-physical formats such as ATMs, plastic cards, ACH fund transfers and electronic billing (Guttmann, 2003). In that respect, the rise of the internet was followed by a wave of development, including financial, as it eases, for instance, information flows and the interaction between economic players, while increasing market volatility (Economides, 2004). On this note, it also gave origin to a new market niche: digital money (Bartos, 2015; Guttmann, 2003).

Cryptocurrency is an umbrella term for any purely virtual currency. It operates in decentralized networks, and as the name suggests, it employs cryptography, being secure, for instance, against counterfeit and double spending. It is also independent of central authorities and banks. All these make it distinguishable from traditional currencies ('Analysis on Crypto-Currency', 2017; Antonopoulos, 2015; Bartos, 2015; Hamayel & Owda, 2021). In addition, these are considered key to commercial and financial industry prospects (Pintelas et al., 2020). Therefore, if it were possible to accurately forecast such values, these could be used to assist in research, policies' definition, and investments, the latter potentially leading to higher profits. This led to an increase of interest in predictive modelling in this field (Pintelas et al., 2020; Yenidoğan et al., 2018).

Nowadays there are several cryptocurrencies, though it is not uncommon for them to die out after some time. However, this is not always the case, as some have become quite prominent. This is the case for Bitcoin (Bartos, 2015; Hamayel & Owda, 2021). Bitcoin, as the object of this study, is the most well-known cryptocurrency in the world and holds value mainly because the users trust it and accept it as viable means of conducting transactions (Yermack, n.d.).

Bitcoin price values from the very beginning have been through several peaks and decreases. According to (Caporale et al., 2019), sharp price declines have occurred six times in June of 2011, January of 2012, April 2013, November 2013, December 2017 and in early 2018, having he latter followed a price rise above 20 times. In this context, a study in 2019 claims that more than half of Bitcoin's transactions (approximately 65%) occurred in 2017 or later, which led to a price increase of

1324% from the beginning to the end of that year. This made Bitcoin stand out, consequently leading to its rise in popularity (Catania & Sandholdt, 2019). However, proportionally speaking, the greatest increase took place in 2013 with a percentage of return of 5,870%, whereas in 2017, the growth was comparatively lower at 1,338% (Ph.D, n.d.).

Bitcoin itself consists of a decentralized P2P network, known as the Bitcoin protocol, and its blockchain (Antonopoulos, 2015; Pintelas et al., 2020). It has a decentralized transaction verification system, and its issuance depends on distributed mining. The latter, along with purchasing or exchanging, are currently the only ways of obtaining Bitcoin. Users prove ownership using keys, and any member of the network can operate as a miner, being such functions regulated by the Bitcoin protocol. Participants in the mining process compete to create and validate blocks on the Bitcoin blockchain in exchange for Bitcoins (Antonopoulos, 2015; DeVries, 2016).

Every 4 years, the rate of creation of Bitcoin is halved, which makes it disinflationary, consequently setting limits to the number of Bitcoins that will come into existence. It is widely known that number of Bitcoin in circulation is expected to follow an easily predictable curve that reaches the objective of 21 million by the year of 2140 (Antonopoulos, 2015; Meynkhard, 2019).

On top of the previous phenomenon, Bitcoin's price is influenced by many other external factors such as the users' financial situation and eagerness to invest, countries' economic picture, and popularity through the word of mouth, news, social media, and other platforms (Catania & Sandholdt, 2019; Kaplan et al., n.d.). Political factors also play a role on this ('Analysis on Crypto-Currency', 2017; Mensi et al., 2019; Mudassir et al., 2020). As an example, its growing affluence led to governments starting to apply some level of legislation to its transactions, such as tax and AML/CFT laws in most of the European Union, while some chose to ban it (*Regulation of Cryptocurrency Around the World: November 2021 Update*, n.d.). Another example is global crisis with economic repercussions such as the Covid pandemic (Garlapati et al., 2021; Mudassir et al., 2020; Umar et al., 2021). However, these types of events are extremely difficult, if not impossible, to capture in data that could be used to feed the models and make predictions.

A study concerning cryptocurrencies and fiat currencies concluded that cryptocurrencies price fluctuations are strongly influenced by those of fiat currencies (Levulytė & Šapkauskienė, 2021). Another one addresses the correlation between bitcoin and precious metals in terms of their volatility. It revealed that Bitcoin is susceptible to precious metals markets' events, being palladium and gold the most influential (Mensi et al., 2019).

All these not only portrays Bitcoin as very flexible, but mostly highly volatile, making it hard to predict. This is considered one of its greatest setbacks on investments (Hamayel & Owda, 2021; Mensi et al., 2019; Pintelas et al., 2020). Regardless, the increase on demand and necessity of some type of support system to the decision-making process of investors, makes it extremely important to try to identify and understand patterns and forecast Bitcoin's value (Wolla, n.d.).

As means to address the problem at hand, different experiments and solutions have been developed and optimized through time. In this setting, indicators such as "Moving Average", "Mayer Multiple", "MVRV Z-Score" and "Reserve Risk" were used to perform price analysis "(*CBBI - Colin Talks Crypto Bitcoin Bull Run Index - BTC Price Evaluation*, n.d.; *The 5 Best Tools for Fundamentals Based Bitcoin Price Analysis - Brave New Coin*, n.d.). "Brave New Coin" is itself a company in that market that provides a variety of blockchain and cryptocurrency-related services and products. In addition, the statistical tool "Stock to flow" was developed to infer the price of Bitcoin. It is based on the hypothesis that Bitcoin is comparable to commodities and precious metals, and that it can be estimated based on the number of bitcoins available in the market relative to the amount being produced by mining each year (*Stock-to-Flow Model*, n.d.). Other solutions could be through predictive modelling.

The Bitcoin price can be deemed a time series, and therefore different types of models, such as Statistical, ML and Vector can be used to predict it. Research indicates that the ARIMA model is commonly employed in time-based analysis, including for predicting trends in investment assets such as stocks and cryptocurrencies. Examples of such can be found in the studies (Rizkya et al., 2019) and (Garlapati et al., 2021) which concern respectively forecasting the demand in a distribution centre and the stock market values, as well as in (Yenidoğan et al., 2018) which is directed to Bitcoin.

However, for cryptocurrencies in particular, Neural Networks models seem mostly used. In this context, LSTM models were applied in the studies (Hamayel & Owda, 2021)**,** (Pintelas et al., 2020)**,** and (Mudassir et al., 2020) which all aimed at predicting Bitcoin. The first two mentioned also targeted Ethereum, as well as Litcoin and XRP respectfully. The three previous studies also included implementations of the GRU, bi-LSTM and CNN models. Furthermore, (Mudassir et al., 2020) also applied the ANN and SANN models. Another case of such was (Tata, n.d.) which resorted to ANN to predict the price of Bitcoin alone. On this note, (İcan & Çelik, 2017) analysed the performance of Neural Networks models on stock market prediction and outlined that the combination of ANN with other statistical or ML technique could increase efficiency.

Another model that was encountered with some frequency was the Prophet. It can be found in the studies (Yenidoğan et al., 2018) and (Garlapati et al., 2021), where it is used to forecast Bitcoin values, and even in (Shohan et al., 2022) that combines a LSTM with a Neural Prophet, creating a LSTM-NP to predict the electricity load at a utility-level scale. Though the latter may seem out of scope, it encompasses different models' features that together outperformed the other techniques by themselves, which suggests that hybrid models are more efficient at forecasting. Other models addressed in the studies above include Bayesian regression model with expert correction (Pavlyshenko, 2019) and SVM (Mudassir et al., 2020).

Overall, as means to produce efficient predictive models that forecast the Bitcoin value through time, it is important to tackle the questions: What variables influence the value of bitcoin? What kind of models better forecast the price of Bitcoin?

In this study, I try to answer this necessity by training different prediction models, using historical data of Bitcoin and related variables of interest.

3. DATA & METHODOLOGY

This research follows a multimodal methodology, combining historical data on Bitcoin with other relevant variables, such as exchange-traded fund indices, different commodities, and other currencies. To conduct this project, historical data between 2011 and the end of 2022 was extracted from the platforms Yahoo Finance (*Yahoo Finance - Stock Market Live, Quotes, Business & Finance News*, n.d.) and Macrotrends (*Macrotrends | The Long Term Perspective on Markets*, n.d.). The variables of study comprise Bitcoin, the dependent variable, the indexes VOO and VT, the commodities gold silver and copper, and several currencies (See APPENDIX A). All records of price variables are in the dollar format and all data tables extracted from the same source share a same structure (See Table 1).

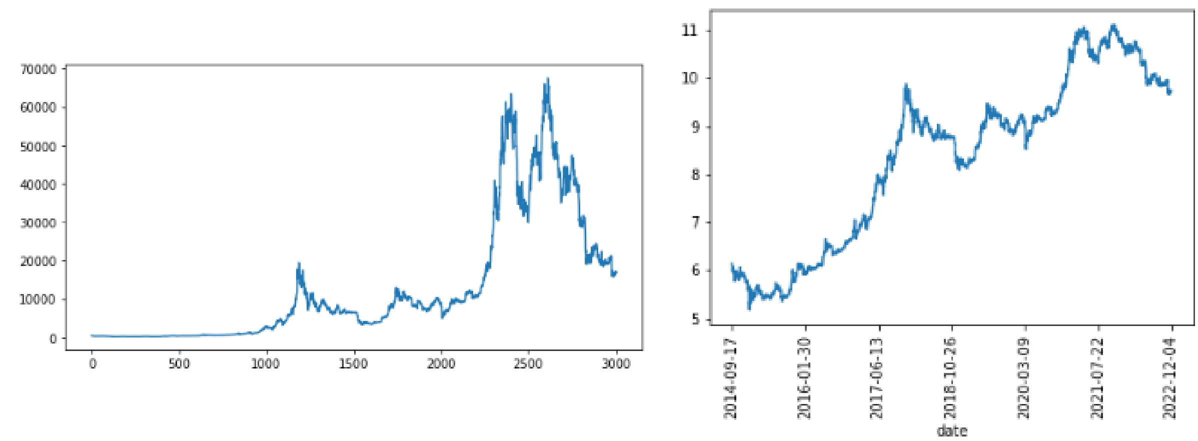
Table 1. Data Structure of Yahoo Finance and Macrotrends datasets.

Column	Description	Source
Date (Y-M-D)	Respective date to that record, which translates the time period into a day	Yahoo Finance
Open	Value at the beginning of the time period	Yahoo Finance
High	Peak value during that time period	Yahoo Finance
Low	Lowest value during that time period	Yahoo Finance
Close	Value at the end of the time period	Yahoo Finance
Adj Close	More accurate value to the time performance	Yahoo Finance
Volume	Number of units traded during the time period, which can be translated into market activity	Yahoo Finance
Year	Respective year to that record	Macrotrends
Average Closing Price	Average Closing Price of the year per pound	Macrotrends
Year Open	Value per pound at the beginning of the year	Macrotrends
Year High	Highest value per pound during that year	Macrotrends
Year Low	Lowest value per pound during that year	Macrotrends
Year Close	Value per pound at the end of the year	Macrotrends
Annual % change	Percentage of change from the before that year	Macrotrends

3.1. Data Understanding

It begun by observing the time frame of the variables of study. Being Bitcoin the dependent variable in this study, its records defined the time window of analysis from17-09-2014 to 04-12-2022, time window. Solely through human eye observation, the Bitcoin time series exhibits various peaks and troughs, seemingly devoid of any discernible pattern. Nonetheless, when compared to the following segment, the initial phase appears to be a relatively stagnant period with low values. This suggests a significant shift in Bitcoin's purchasing trends during its early stages. A discernible pattern and cycle emerge upon closer inspection through a logarithmic plot, displaying recurring phases of growth and contraction. Notably the most significant increase occurs between 2016 and 2017, indicating a period of increased activity and interest in Bitcoin during that timeframe (See Figure 1).

Figure 1. Bitcoin time series plot of the open value as an example, and respective logarithmic plot.



The same plots were generated for the remaining variables. When time series showed questionable curves, these were excluded. This was the case for New Taiwan Dollar Data and the Saudi Riyal Data (See APPENDIX B), it was decided to exclude them before the Preparation phase.

It was then performed the Exploratory Analysis. Although a univariate analysis was performed on every variable, comprising a summary of their structure and descriptive statistics, it was taken into deeper depth when it came to the dependent variable. As one can observe, the Bitcoin dataframe had originally 3001 records, with the 7 columns previously mentioned.

According to the descriptive statistics regardless of the measure, the values “open”, “high”, “low” and “adj close” (hereby referred as Bitcoin’s price variables) are always in the same order of magnitude and consistently quite close to each other, showing a high degree of similarity. The standard deviation (std) is quite high between approximately 15775.847 and 16674.919, which can be translated into significant variability. Altogether supports the claim that there is a substantial dispersion from the mean.

Measures of central tendency and shape were then generated and plotted. For the price columns of Bitcoin, the distribution was proved to be highly positive skewed and leptokurtic. The same type of distribution can be observed when it comes to the volume. Due to the nature of Bitcoin, it is clear to understand that there is a wide range of values and heterogeneity (See Figure 2).

Figure 2. Measurements of shape of Bitcoin's open value (on the left), and volume (on the right), which respectively presented an excess kurtosis of 1.281 and 27.096, and skewness of 1.543 and 2.734.

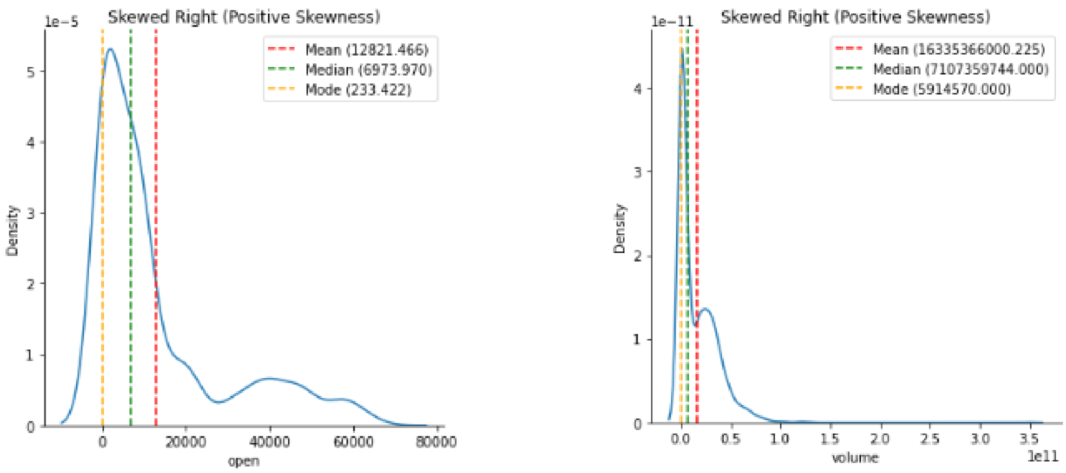
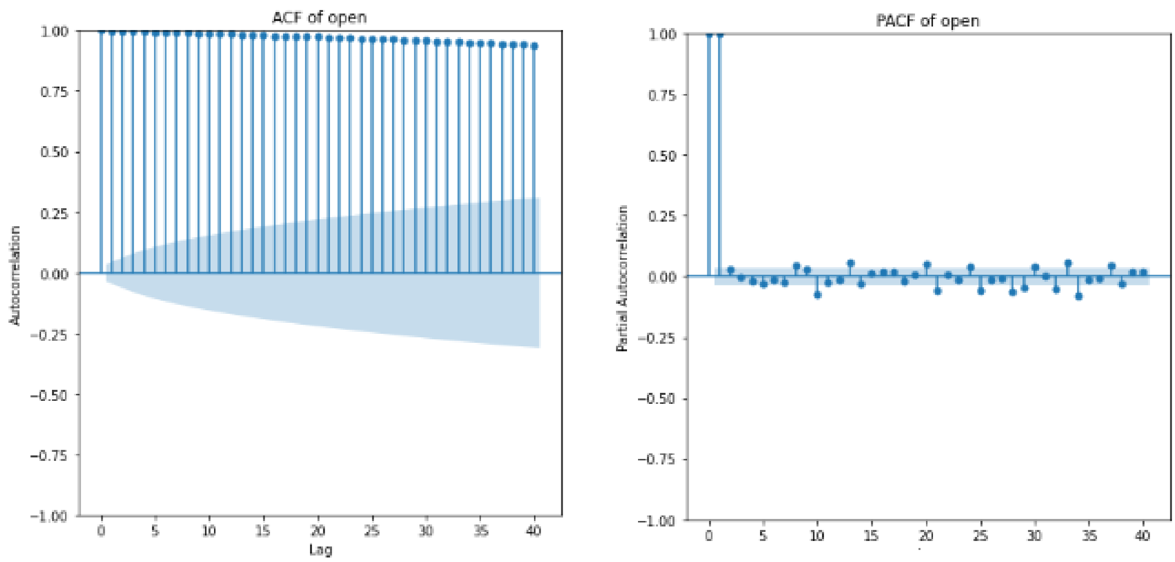


Figure 3. Lollipop plots of Bitcoin's open value through time.



Lollipop plots of ACF and PACF were also created to assess temporal dependencies (See Figure 3). As no visual differences were noticed, the analysis was continued. The ACF lollipop plot lags were all very close to 1, indicating a strong positive autocorrelation. The absence of peaks throughout the lags provides no support to the existence of seasonality. The PACF lags, on the other hand, apart from the first one, are all extremely close to 0 with no significant spikes (See Figure 3). All these together can be signs of a "random walk" with a drift which is of deterministic nature, and therefore the time series can be considered nonstationary, and so it should not be possible to make predictions solely based on historical Bitcoin data. This indicates that other variables apart from Bitcoin itself should be used in the training of the models to achieve better results.

Observing the correlation matrix of these variables, it is safe to claim that we are in presence of multicollinearity, and so only one of the price variables or an aggregation of all should be used to prevent overfitting by feeding the model with repetitive information. All proved to have a positively high correlation to the dates, as well as the volume, varying from 0,71 to 0,76 (See APPENDIX C).

A simple analysis was performed by plotting the Bitcoin's price variables along with the respective moving average (See APPENDIX D), considering the 7, 30, 60 and 200 days prior. It is possible to observe that a window of 7 days led to severe overfitting, while a window of 200 led to severe underfitting. The windows of 30 and 60 avoided the extremes and seemed viable indicators. It was also possible to observe again that it was after 2016 that Bitcoin transactions increased in number and value.

A time-based analysis was also conducted, with the intent of uncovering any patterns underlying the date variable (APPENDIX E). The values displayed several waves of growth and decline, though no type of cycle was detected, apart from great decreases following great peaks, and vice versa, which is not at all surprising. However, it is clear to see that the value of Bitcoin increased a lot from the year of 2014, and then again from 2020. Using both plots and correlation values, considering the year and month instead of the whole date, no months seemed to be significantly more favourable than others either and therefore the time component in date format was kept (APPENDIX F).

To select from the variables of study with the most forecasting potential, these were checked for high correlations (≥ 0.8) with Bitcoin's price variables. I also plotted these values against the Bitcoin's price variables to check for tendencies (See APPENDIX G). In this context, through both visualizations, the most distinguished variables were VT (See Figure 4), VOO, silver, copper, and Israeli New Shekel in descending order. The scatter plots reveal that, although having little to no association with Bitcoin, the Moroccan Dirham, Danish Krone, Euro (See Figure 5), South Korean Won, and Central African Franc seem to portray two sorts of correlations: one that climbs until it reaches a plateau, and one that is positive. It is crucial to emphasize, however, that correlation does not always imply causality or impact between variables.

Figure 4. Correlation matrix between Bitcoin and Vanguard Total World Stock Index Fund (at the top) and scatter plot between Bitcoin's and VT's open values (at the bottom).

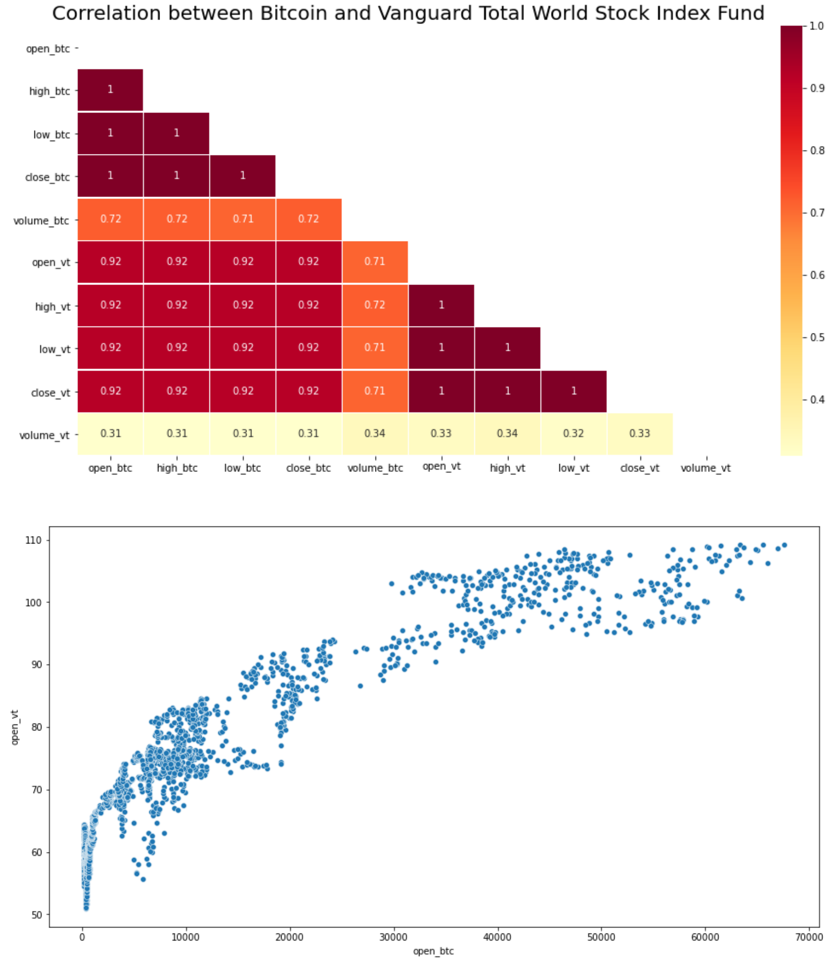
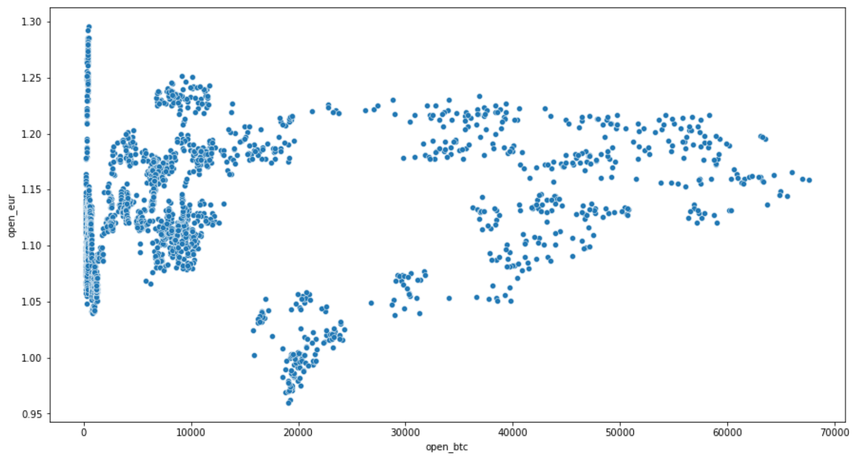


Figure 5. Scatter Plot between the open values of Bitcoin and Euro as an example.



On to the Data Quality Verification there was a coherence check, followed by a missing values check. The bitcoin dataset proved to have no missing dates and to comprise records for all dates in the timeframe. The bitcoin dataset proved to have no missing values either. That was not the same for the Israeli New Shekel and the Euro, who appeared to have, respectively, 6 and 5 missing values, representing a percentage of around 0.19% and 0.16%. The higher percentages did not go above 0.33%, except when addressing the commodities dataframe, with 9 records constituting around 14.3%. No datasets presented duplicates. In addition, it was also calculated that around 28% of the records were before 2017. This year is when there was the greatest change of price until now, influencing the order of magnitude of the values greatly.

Finally, the variables considered useful for the study were stored as means to be treated and prepared appropriately for modelling. These include all but the currencies New Taiwan Dollar Data (TWD) and Saudi Riyal Data (SAR) due to presenting very unreliable records.

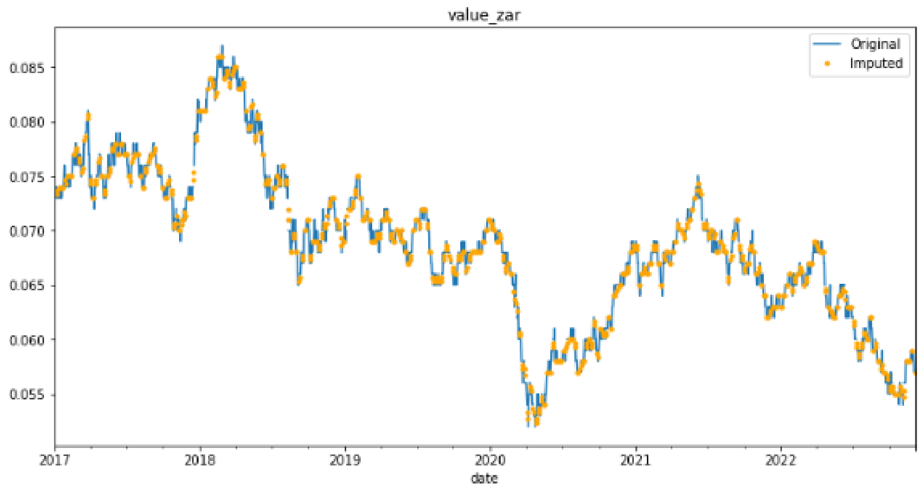
3.2. Data Preparation

All data from the variables of study was joined and merged appropriately on the "date", by keeping every Bitcoin's records. The process to create the new data structure went through calculating the median of "open", "high", "low" and "close" for every price variable, only keeping those and Bitcoin's "volume". Secondly the commodities were merged the same way as previously, this time on the year. The date column was then set as the index.

It was now required to perform a new assessment of the data quality. Starting from the missing values analysis, 27 columns accused the presence of missing values between 858 and 932, which can be translated into approximately 28.59% and 31.06% of the total records. In absolute terms, there were 937 records with missing values.

Given the previous observations in data understanding, which portrays in the time period of the analysis the records before 2017 as outliers, and the fact that the year 2017 is regarded as the start of standardization of cryptocurrencies and Bitcoin's rise in popularity (DeVries, 2016), from here on only data from and including 2017 was kept. This leads to removing quite a great part of the source data (837 records, around 28%), which is not advisable in theory. However, that data is not representative of the present market, since a lot changed since then, from the world to people's perspective, and time-based models could easily be wrongly influenced by outdated tendencies and events. On top of all that, the removed set still included a lot of missing values. There were then, on the same columns, between 619 and 673 records with missing values, representing approximately from 28.60% to 31.10%. In absolute terms, there were 678 records with missing values. It followed the treatment of the mentioned missing values. There were applied three different methods of filling them in: linear regression, linear interpolation (See Figure 6), and polynomial interpolation. The first method was visually the least successful, as the choices for treatment did not follow the curves of the plots at all. On the other hand, though different, the second and third method produced quite similar values, seemingly more accurate. Therefore, both were techniques applied and the outputs kept in two separate dataframes, to later join to diminish the different treatments' error and noise.

Figure 6. Example of treatment of missing values through linear interpolation by plotting the original and imputed values of South African Rand



When re-accessing once again the number of missing values, the dataframe where linear interpolation was performed still presented the 01-01-2017 and 02-01-2017 records with missing values (2 each). The dataframe where polynominal interpolation was applied had 4 records with missing values instead, respective to 01-01-2017 and 02-01-2017 with 2 each, and 03-12-2022 and 04-12-2022 that were associated with 7 and 20 respectively. In both cases, the reason for missing values persisting is most likely due to these records being in sparse data regions, which makes them more isolated and harder to make estimations. Taking this into account, the record 01-01-2017 was deleted and 02-01-2017 was filled in with the value of the following day. 03-12-2022 and 04-12-2022 were filled in with the ones from linear interpolation.

With all the missing values resolved, a new prepared dataframe was created by calculating the average of those two sets together. The index was also associated to a daily frequency, enabling predictive models to recognise it as time-based. This way, it was ready for modelling.

3.3. Data Modelling and Evaluation

This phase consisted of using the previously prepared data to create predictive models to forecast the value of Bitcoin. The process started with organizing training and testing sets and setting a seed to remove the randomness factor, ensuring reproducibility. In this regard, the training and a testing set were populated with records prior and post 2022 respectfully, and the seed was defined as 42. For certain model types, the data received additional transformations and treatments. Models were then fitted to the training set, and their predictions were plotted against test sets. Long-term forecasting was also performed when feasible (See Table 2).

Upon research and different experiences and try outs, four different types of models were created: ARIMA models, VAR models, RNN models with LSTM Layers and Prophet models. ARIMA and VAR represent the more traditional statistical approaches. RNN is a type of ANN designed to deal with sequential data, while LSTM is a type of RNN capable of capturing long-range dependencies (*Recurrent Neural Network - an Overview | ScienceDirect Topics*, n.d.). On the other hand, Prophet is a free and open-source forecasting software developed by Facebook. It is particularly good at predicting time series data because it incorporates non-linear trends, weekly and yearly seasonality, and holiday handling. Its ability to handle missing data, detect trend shifts, and accommodate large outliers without manual intervention is one of its key strengths. The software is designed for business forecasting, with scenarios including time-based, daily, and weekly observations over the course of a year. Large outliers, trend changes, missing observations, and non-linear growth curves are effectively addressed (Yenidoğan et al., 2018).

Through feature selection, the variables considered to have the most potential were organized into all the possible combinations, and then fed to the models accordingly. The variables in this set are "volume," "value_vt," "value_ils," "value_eur," "value_silver," and "value_copper." When combined with Bitcoin (excluding individual consideration), these form 6 combinations with one variable, 15 combinations with two variables, 20 combinations with three variables, 15 combinations with four variables, and finally one combination with all six variables (See APPENDIX H).

Starting on from the ARIMA models, it is important to outline that given its nature, only the Bitcoin variable was considered, apart from the date component. Several steps took place, including assessments using once again the lollipop plots of ACF and PACF upon the training set, which were no different from the ones in Data Understanding.

However, this time the ADF test was also performed as means to validate the previous claims. A p-value of approximately 0.842, which surpasses the typical significance level of 0.05, supports the previous conclusions. To mitigate the influence of nonstationary features of the data, differencing was applied, pulling it closer to being stationary, and consequently making it easier to forecast (See Figure 7).

Observing the new lollipop plots generated (See Figure 8), the greatest change is in the ACF plot, which now presents the first data points of values 1 and 0.5, followed by a sudden drop from where the values are all close to 0, some positive, some negative interchangeably. The PACF did not change substantially, only portraying a more gradual decline than before. The p-value decreased greatly to approximately 3.019e-13. Taking all into account, the differencing was deemed successful.

Figure 7. Differenced train set plot for ARIMA modelling.

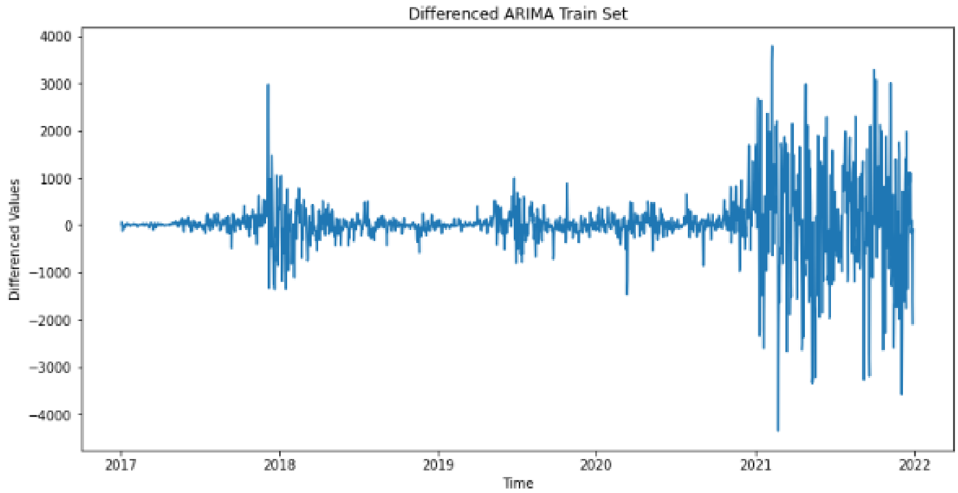
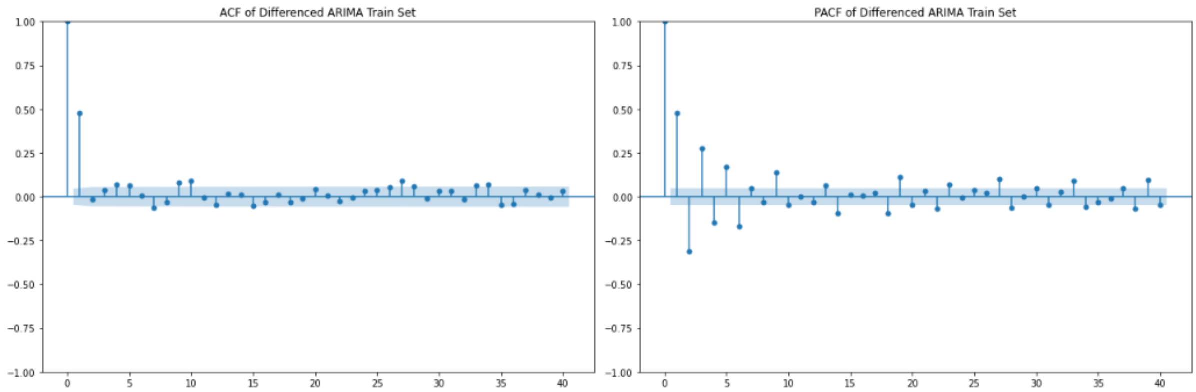


Figure 8. Lollipop plots of the differenced train set plot for ARIMA modelling.



Two models were then created, one using the differenced training set and the other using the original training set. In both cases, p was set to 30 and q to 1. However, in the first case d was set to 0, since the dataset had already been previously differenced, while in the second case d was set to 1.

Next, a respective summary of the statistics was generated for each of the models, as well as the plot. When it came to the predictions using differenced data, it was required to first reverse the differencing operation by resorting to cumulative summing.

Going on to the VAR models, each model was created and fitted for a lag order, ranging from 1 to 30. Then the AIC was extracted from the output, as means to uncover the best lag order. A new model would then be created with that optimal lag. The AIC and BIC plots were then displayed, followed by the regression results summary, a correlation matrix of the residuals, and a plot portraying the predictions against the test set.

The RNN models (a type of ANN) with LSTM Layers, seeming to be more reliable, went through a more extensive approach. Not only were the predictions analysed for each combination, but also considering different prediction days, more precisely, 7, 30, 60 and 200.

This said, for each combination and number of prediction days, the data was scaled using MinMax, and the values respective to that set of days were used as input. The RNN models have a sequential nature, encompassing 3 LSTM layers of 50 neurons, each followed by a moderate Dropout layer of 0.2, and the final output layer. The adam optimizer and the mean squared error was used as loss function when compiling. When fitting, 25 epochs and a batch size of 32 were set. Afterwards, the model was used to make predictions on the test set. Due to the scaling, the predictions had to be reversed back. Then they were plotted against the test set and evaluated using the metrics MAE, MSE, RMSE and R^2. The one day in the future was also forecasted.

Finally, on to the Prophet models. These were created by Facebook and was selected since it is intended to face seasonality and holiday effects, while dealing with time series that display varied patterns, go through trend shifts.

For starters, the index and target columns had to be renamed to ds and y respectfully. Also, every model had to be set with daily seasonality. The focus was then on the target variable alone, and after appropriate training and fitting, predictions were generated for the test set and for the next 1000 days. Different plots were then generated displaying them, the trend throughout, the weekly, yearly, and daily patterns, as well as the change points.

On a second phase, the previous variables recognised as having the most potential were integrated as regressors, in the same combinations prior. Once again, the plots of the forecasts were displayed, but this time also followed ones with the performance metrics MSE, RMSE, MAE, MAPE, and Coverage. These were calculated upon performing crossing validation of the models, which considered an initial training period of the most recent 730 days, 180 days of training per iteration, and was predicting for the following 338 days.

Globally speaking, the metrics AIC, BIC and HQIC were used to evaluate the ARIMA and VAR models by finding the best compromise between fit goodness and model complexity. These are more appropriate for simpler statistical models, reason why these were not chosen to evaluate the RNN and Prophet models, which are respectfully more complex with less explicit parameterization, and too different in terms of design and objectives from traditional models. The summary of results of ARIMA and VAR also included other different measures addressed in more detail in the results section. On the other hand, RNN and Prophet were evaluated in common by MSE and RMSE, which are meant to assess the accuracy of predictions by measuring the average squared difference between predicted and actual values. On top of that, R^2 was used to evaluate the RNN models to compliment the previous evaluation, even though it is usually used to determine linear regressions' goodness of fit. On that note, Prophet was evaluated additionally through MAPE and Coverage for point forecast accuracy and assessing the reliability of prediction intervals respectfully.

Having predictions, Flask was used to build a simple web application as PoC, that creates a root and returns the predictions in json format, so that the backoffice of the website can fetch them.

Table 2. Models' inputs and hyperparameters

Models	Additional Data Treatment	Hyperparameters
ARIMA	Differencing and removal of consequential missing values	order: p=30, d=0, q=1
	-	order: p=30, d=1, q=1
VAR	-	default
RNN with LSTM Layers	MinMax Scaling of feature_range=(0, 1)	LSTM: units=50 Dropout(0.2) Dense: units=1 optimizer="adam", loss="mean_squared_error" epochs=25, batch_size=32
Prophet	Reset index Rename the columns 'index' to 'ds' and 'value_btc' to 'y'	daily_seasonality=True changepoint_range=0.8
		daily_seasonality=True changepoint_range=0.9

4. RESULTS AND DISCUSSION

The variables considered to have the most predictive potential were Bitcoin volume, the VT index, Israeli New Shekel, Euro, silver, and copper, being the ones used as models' inputs. These were the ones that best performed in the data understanding in terms of being correlated to the value of Bitcoin. Euro was selected above the others of the same context due to being used by multiple countries part of the European Union.

Starting from the ARIMA models, two were generated using a differenced and non-differenced dataset prior to fitting. Both presented a poor performance, as one can observe from both the statistics and plots (See Table 3 and Figure 9). In comparison, the predictions made from the original training set had a higher Log Likelihood and Prob(Q), while keeping a lower AIC, BIC and HQIC. Though such differences were subtle, these can still be considered the most reliable.

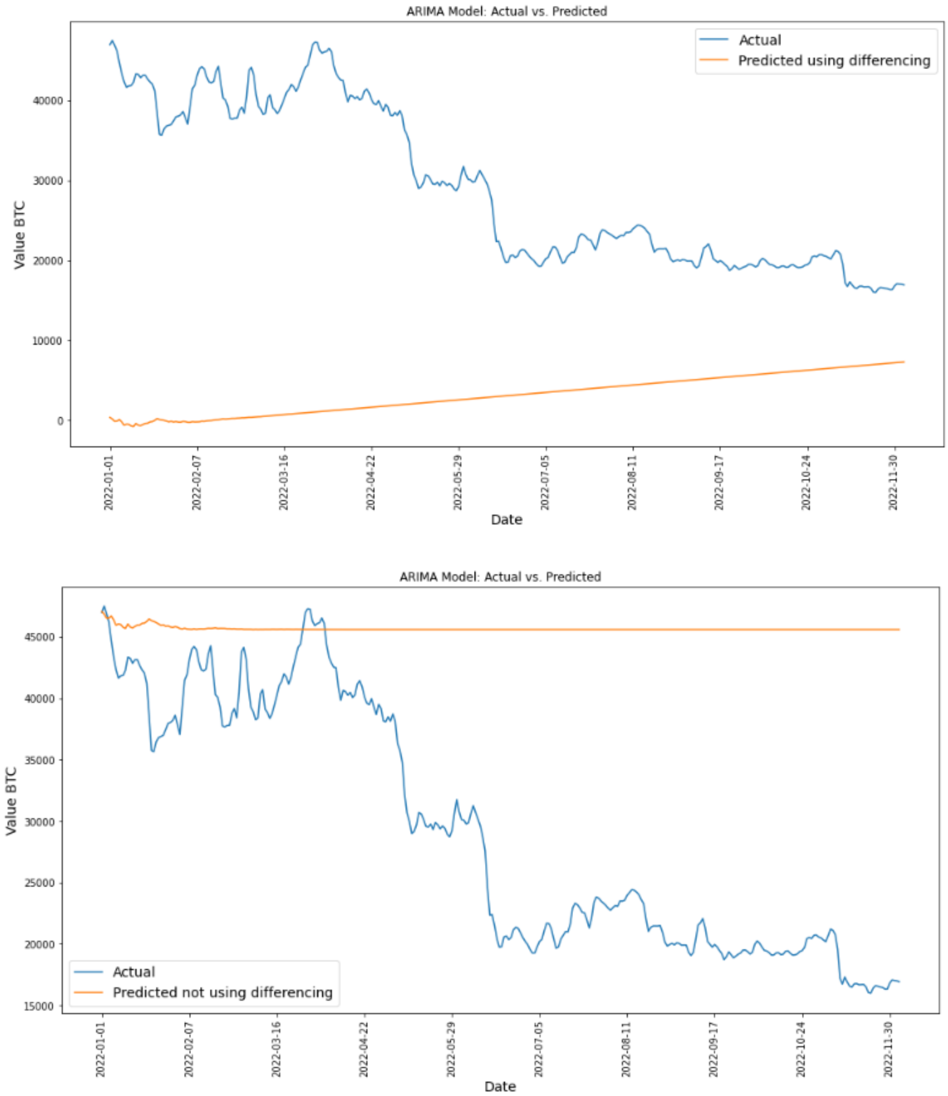
Table 3. Evaluation results on ARIMA models fit with the differenced and original training sets.

	Differenced Training Set	Original Training Set
Log Likelihood	-13806.735	-13807.145
AIC	27679.470	27678.289
BIC	27861.260	27854.570
HQIC	27746.531	27743.318
Covariance Type	opg	opg
Ljung-Box (L1) (Q)	0.01	0.00
Prob(Q)	0.94	0.96
Heteroskedasticity (H)	11.04	11.04
Prob(H) (two-sided)	0.00	0.00
Jarque-Bera (JB)	8846.70	8859.88
Prob(JB)	0.00	0.00
Skew	-0.10	-0.10
Kurtosis	13.79	13.80

Both sets of predictions share the same heteroskedasticity, which is quite high. These also share a same Prob(H), which is expected given this parameter assures the existence of heterogeneity itself. However, being 0 can result from some overfitting.

The Jarque-Bera (JB) value is higher on the predictions made from the original training set, meaning these is closer to a normal distribution than the others. Its test statistic is 0 in both cases, which shows that the observations perfectly meet the assumptions of the normal distribution, with no window of error. This also aligned with the skewness value, which makes portrays a very slightly tendency to the left. The value of kurtosis, on the other hand, are not the exact same but very close to, and show a leptokurtic tendency.

Figure 9. Plots of ARIMA Models' using the differenced (at the top) and original (at the bottom) training sets.



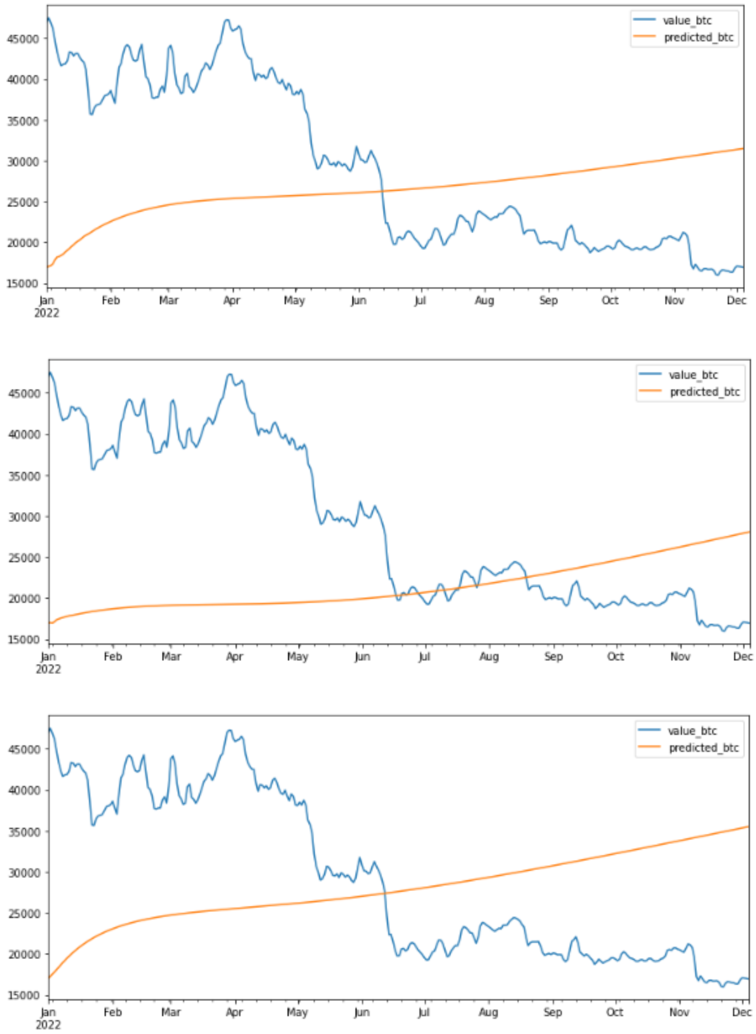
The plots support the previous claim that the predictions made from the original training were more accurate, since they seemed closer to the real values. Still, this does not imply the results were positive on this case. On top of that, considering that there might be some overfitting, the results are far from satisfactory. Both models were, therefore, proven to be not at all feasible. This came to no surprise, especially given the fact that only the target variable itself, the value of bitcoin, can be used to make the prediction. That is why using the VAR instead would in theory produce better results.

For every combination, the VAR model with optimal lag were generated. Unfortunately, these did not perform as well as expected (See Table 4). For each case, the method OLS was used, and equations equivalent to the number of variables in the combination were generated. Out of the 63 were created, only the results from the top 3 are displayed, which regard respectively from the top 6, 5 and 5 variables.

Table 4. Global evaluation results from the VAR models.

Measure	Nobs	Log Likelihood	AIC	BIC	HQIC	FPE	Det (Omega_mle)
Max	1821	8797	58.210	58.583	58.348	1.91E+25	1.78E+25
Min	1795	-58439	-25.179	-24.398	-24.891	0	0
Median	1815	-35701	20.868	21.481	21.094	1.16E+09	1.03E+09
Average	1812	-25345	16.845	17.427	17.060	3.94E+23	3.62E+23

Figure 10. Predictions' plots of the top 3 VAR models from the third to first position.



The first metrics to consider were the AIC, BIC and HQIC. When sorting from smallest to largest per metric, the models were the same and in the same order. Apart from the target variable, their respective combinations all included the Israeli New Shekel, Euro, and Copper. The differences were, starting from the third position, the index VT, Silver for the second position, and both the index VT and Silver for the first position. Looking at the Log Likelihood and FPE, the previously established order suffers no alterations, supporting it.

The residuals correlations were all mostly around 0, which is a positive sign. However, the models in 2nd and 3rd position presented correlations of approximately 0.68 between silver and copper Though this is understandable due to the nature of the variables, it is surprising how it scored so high on the above metrics. The model in 3rd position, presented a correlation of approximately 0.13 between the Bitcoin and the index VT and 0.21 between the Euro and the Israeli New Shekel. For further detail, check APPENDIX I.

Looking at the predictions' plots (See Figure 10), one can observe that they are not extremely different, being the one is position 3 highly like the one considered to be the best. It is possible to claim that there were no feasible models created using VAR.

On the other hand, the RNN models with LSTM layers proved to be feasible, as expected, though with the restraint of only being able to predict maximum until tomorrow. The data was scaled prior to fitting, and then models were generated for Bitcoin itself and the whole combinations.

Observing the global statistics of the evaluation metrics (See Table 5), the best MAE was of 675.975, the best MSE was of 342606, the best RMSE was of 943, and the best of R2 was of 0.972. It is relevant, however, to pay some attention to the minimum R2, as such values usually lie between 0 and 1. The fact that it is below 0, and by such a large margin, suggests that there is at least a very misleading model. Taking this into account, it is important to take a closer look at the remaining statistics of this metric. When looking at its average and median, which were both between the expected threshold, the latter being extremely close to the best value, it is possible to claim that most models were not compromised.

Table 5. Global evaluation results from the RNN with LSTM Layers models.

	MAE	MSE	RMSE	R^2
Max	6373.651	42835574	6545	0.972
Min	675.975	342606	943	-7.653
Average	1903.884	6941193	2360.233	0.580
Median	1426.012	3933610	1983.332	0.946

In a higher-level perspective considering the number of prediction days, the statistics are as follows below (See Tables 6, 7, 8 and 9). Considering MAE, MSE and RMSE, the maximum value increases with the number of prediction days. The same applies to R^2, though only until 200 prediction days since the values drop to even lower than at 7 prediction days. The minimums, on the other hand, all decrease, except for RMSE on the 200 prediction days, which subtly increases. Since an increase in the number of prediction days results in less biased models, these tendencies seem rather accurate. The only real outcast in this scenario are models considering 200 prediction days. Taking a closer look at this table, it is possible to observe that the values out of the usual range of R^2 are only associated to these models. All this supports the previous claim of them being unreliable.

Table 6. Evaluation results from the RNN with LSTM Layers models considering 7 prediction days.

	MAE	MSE	RMSE	R^2
Max	2862.163	10999597	3316.564	0.964
Min	1289.027	3549336	1883.968	0.887
Average	1694.596	5105189	2232.624	0.948
Median	1615.829	4516774	2125.261	0.954

Table 7. Evaluation results from the RNN with LSTM Layers models considering 30 prediction days

	MAE	MSE	RMSE	R^2
Max	5471.761	36817863	6067.773	0.970
Min	1172.605	342606	1678.978	0.607
Average	2305.583	9622527	2829.788	0.897
Median	1621.424	4918835	2217.837	0.948

Table 8. Evaluation results from the RNN with LSTM Layers models considering 60 prediction days.

	MAE	MSE	RMSE	R^2
Max	5505.644	37437067	6118.584	0.972
Min	1057.219	2348128	943.318	0.554
Average	1709.671	5832699	2223.919	0.930
Median	1306.002	3509394	1866.037	0.958

Table 9. Evaluation results from the RNN with LSTM Layers models considering 200 prediction days.

	MAE	MSE	RMSE	R^2
Max	6373.651	42835574	6544.889	0.812
Min	675.975	930916	964.840	-7.653
Average	1905.686	7204357	2154.601	-0.455
Median	1071.789	1745372	1321.123	0.648

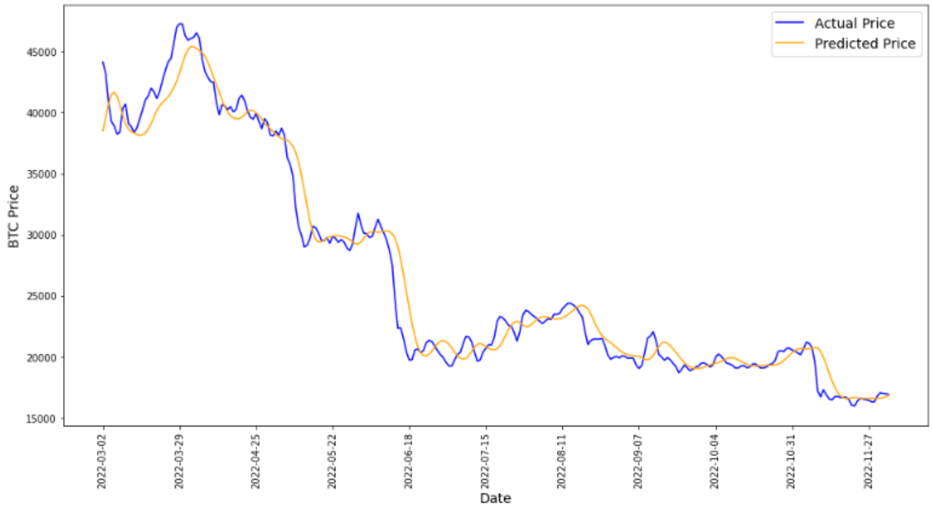
Focusing on the other tables there is a difference of 23 days between 7 and 30, and of 30 days between 30 and 60. 23 is lower than 30, and yet the statistics on the metrics are closer between the models considering the previous 30 and 60 days. Between them, the latter seem to be more feasible. The models based on the previous 7 days, though apparent to be better, are also more prone overfitting. The focus on the analysis was therefore set to the ones considering the previous 60 days to make forecast.

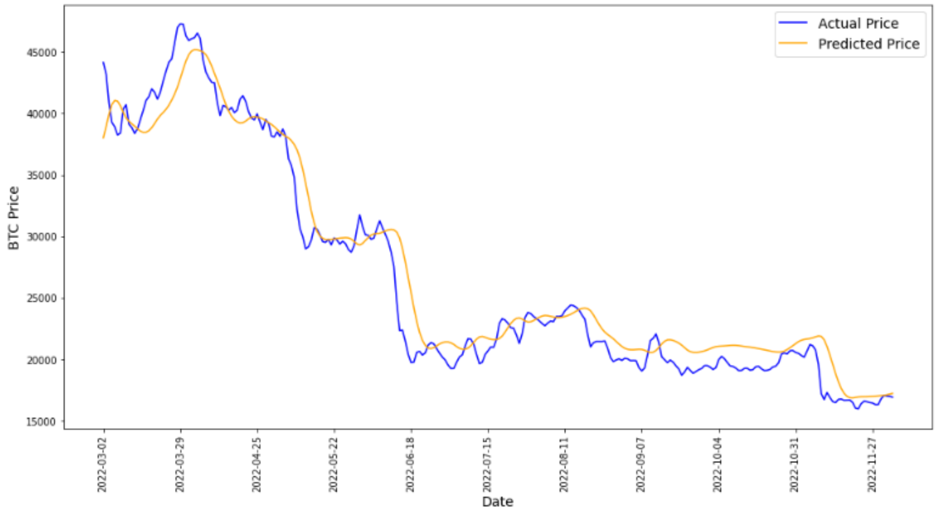
Out of the previous selection, and considering one metric alone, for MAE the top 3 models were the ones with the variables Bitcoin and Volume, then Bitcoin alone, followed by Bitcoin, Volume, Israeli New Shekel, and Silver. For MSE and R^2, these were using Bitcoin and Volume, then Bitcoin, Volume, and Israeli New Shekel, and lastly Bitcoin. For RMSE, these were the ones using Bitcoin, VT, and Copper, then Bitcoin and Volume, and at last, Bitcoin, Volume, and Israeli New Shekel. Similarities are quickly spotted since the same winning variables mostly persist, even though not necessarily in the same order. However, in none of them were the scores the highest for when Bitcoin is by itself, which proves predictions are more accurate when considering external variables at least in this case considering the combinations. For further detail, check APPENDIX J.

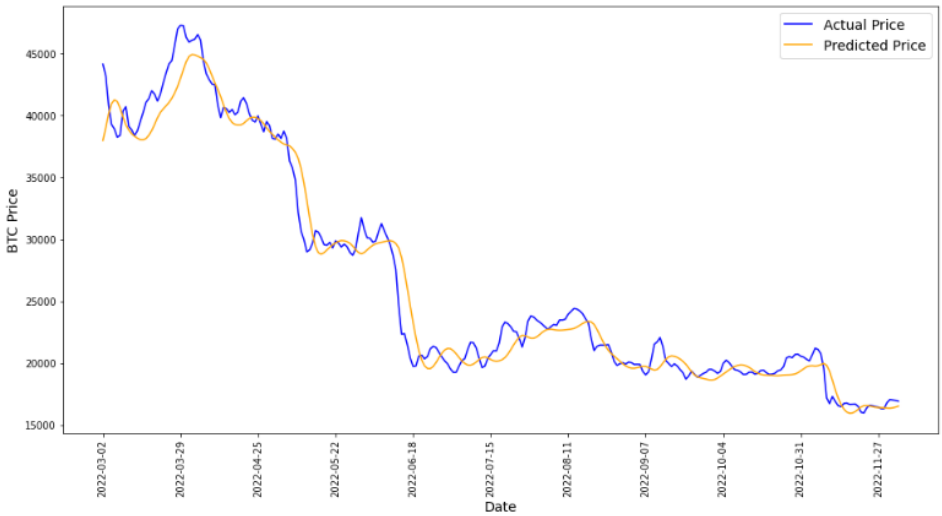
In order to better discern which of the models seem more successful, the respective plots were compared. Note that for 60 predictions days, the forecasts were made for the period between 02-03-2022 and 05-12-2022, including.

The plots all look extremely similar (See Figure 11), and due to their nature, they seem to predict with a lag. However, the most similar ones are the one using only Bitcoin and the one using both Bitcoin and Volume, as well as the ones including both Volume and Israeli New Shekel. The first case can be explained by the fact that Volume and Bitcoin are most likely interdependent on one another, and therefore Volume's influence in the behaviour of the model would not be significantly different from the one using Bitcoin alone. For the second case, the reason is most likely sharing variables that seem to have the most influence on the models' behaviour.

Figure 11. Predictions' plots of the RNN models with LSTM Layers considering 60 prediction days and the variables Bitcoin (at the top), Bitcoin, VT, and Copper (in the middle) and Bitcoin, Volume and Israeli New Shekel (at the bottom).







The predictions for the following day in the future, meaning the date of 05-12-2022, ordered in the same way as the models, were approximately 16834, 17183, 16807, 17062 and 16707. Given that for the day, the actual values were around 17129 when it opened and 16975 when it closed, with the highest being around 17378 and the lowest 16922, the only models that predicted inside those ranges were the ones using only Bitcoin and Volume, and using Bitcoin, Volume, and Israeli New Shekel. The first mentioned was closer to the highest value, while the second was closer to the lowest.

Although these models work for the immediate future, as they can predict one day based on the x previous ones. However, this can also be interpreted as not being able to predict the future at all in the sense that, as it predicts with a lag that future day prediction reflects the day before. An experiment was conducted so that predictions were considered instead of the actual values for the sets of prediction days in the future, since these were yet to exist. This proved to be fruitless, as the error propagates and curve stagnates quite early, always presenting the same prediction value afterwards, providing a false and excessive sense of stabilization of Bitcoin. All the above is evidence that these models are long term ineffective.

On to the Prophet models, these initially utilized only Bitcoin as the primary variable in the study, and then incorporated the remaining as regressors. On to the Prophet results, the predictions were returned on a dataframe presenting the specific format (See Table 10). Considering Bitcoin itself the only variable in the study, the plots resulting from using solely bitcoin to make predictions against the testing set were displayed below. Looking at the predictions (See Figure 12), it is possible to observe a clear increase associated with small declines. Though looking at the tendency, it could have been so, that timeframe portrays a suddenly high drop. Probably it was due to some external factor out of our reach of this analysis. In this context, change points using a 0.9 range were identified right at the end and beginning of 2018, close to the beginning and the middle of 2019, on the first and third quarter of 2020, and right before the beginning of 2021, and three times, with the same distance, on the first half of 2012.

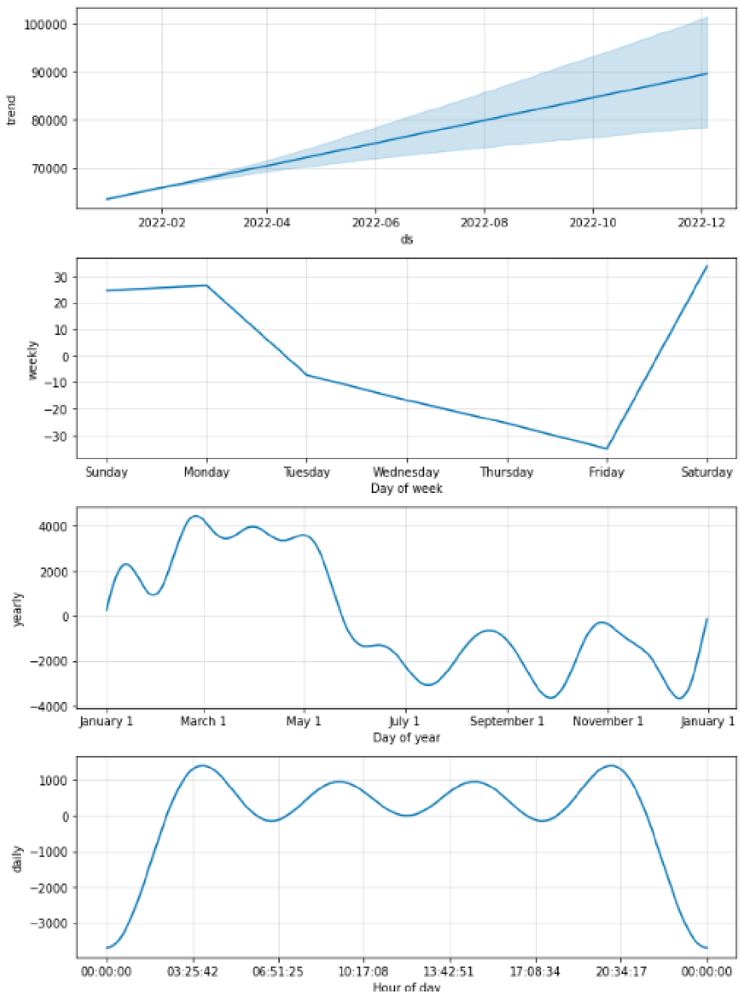
In Figure 13, the trend plot displays that Bitcoin has a general tendency to increase, the variance of it increasing through time. Weekly speaking, the value appears to be at its lowest on Fridays, remaining almost static and the highest during the weekends, being the decreasing more accentuated from Monday to Tuesday, and then less until Friday. The yearly trend portrays something close to inverting, since from January to July the curve was increasing and declining swiftly and interchangeable, remaining mostly higher, while afterwards it is the opposite, with more significant ups and downs. The daily trend also displays up and downs of no grand discrepancy, while representing 4 peaks, one around 3:30 a.m., another around 8 a.m., a third around 3p.m., and the last close to 8:30 p.m.

Table 10. Output dataframe's structure from Prophet models.

Column Name	Description
ds	Date of the record
trend	Overall trend in the time series
yhat_lower	Lower bound of predictions
yhat_upper	Upper bound of the predictions
trend_lower	Lower bound of the trend
trend_upper	Upper bound of the trend
additive_terms	Additional components added to the trend
additive_terms_lower	Lower bound of the additive terms
additive_terms_upper	Upper bound of the additive terms
daily	Daily seasonality
daily_lower	Lower bound of daily seasonality
Daily_upper	Upper bound of Daily seasonality
weekly	Weekly seasonality
weekly_lower	Lower bound of weekly seasonality
weekly_upper	Upper bound of weekly seasonality
yearly	Yearly seasonality
yearly_lower	Lower bound of yearly seasonality
yearly_upper	Upper bound of yearly seasonality
multiplicative_terms	Factors or effects that influence the time series
multiplicative_terms_lower	Lower bound of multiplicative terms
multiplicative_terms_upper	Upper bound of multiplicative terms
yhat	Predictions

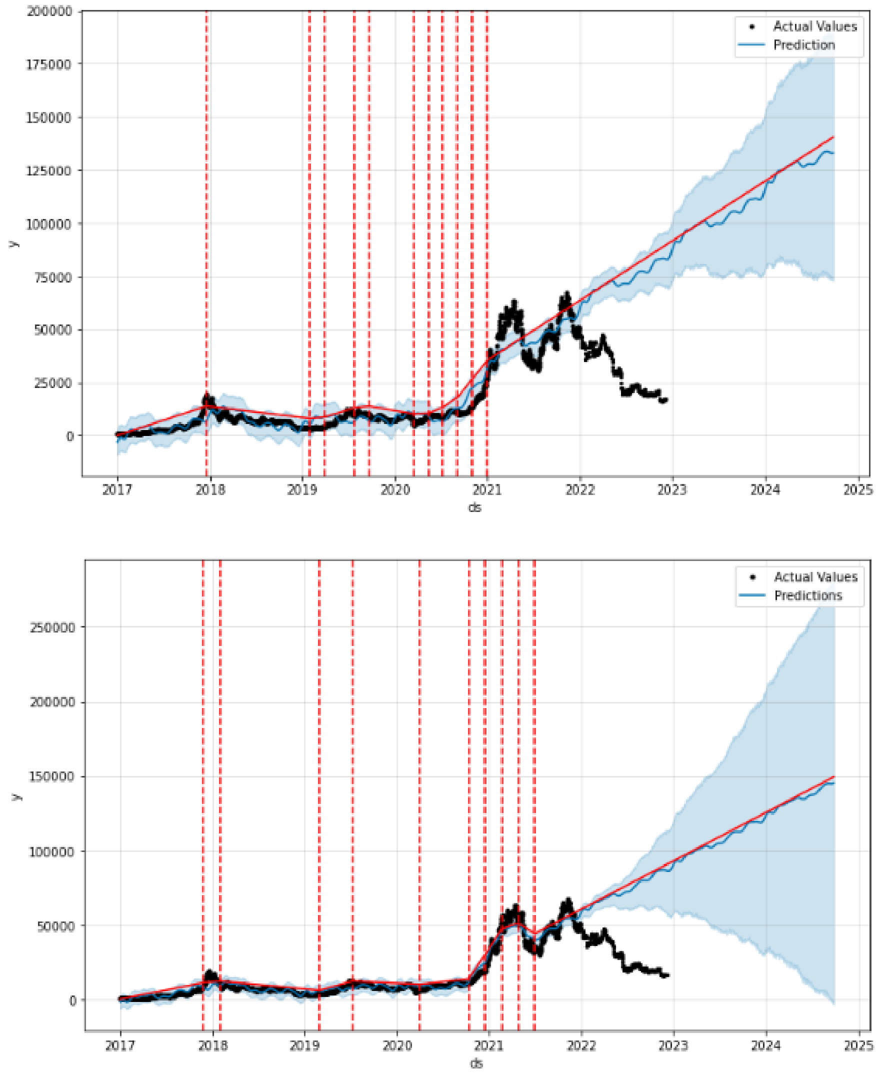
Figure 12. Plot of Prophet model's predictions, using only Bitcoin as input, against the test set with changepoints in red

Figure 13. Plots of Prophet model's global trend, weekly, yearly, and daily, using only Bitcoin as input.



Taking a closer look now at the results from longer term predictions (See Figure 14), it is possible to observe more clearly once again the growing curve, with increasing margin of error as times goes on. Considering the range of 0.8 for change points, significant discrepancies were detected right at the beginning of 2018, 4 times during the year of 2019, and 6 between the year of 2020 and beginning of 2021. Increasing the range back to 0.9, one can observe the variance growing immensely as in comparison to the prior case. The resulting changepoints are also identical to the ones identified when predicting against the test set.

Figure 14. Plot of Prophet model's predictions in the long future (until the beginning of 2025), using only Bitcoin as input, with a range for change points of 0.8 (at the top) and of 0.9 (at the bottom). Changepoints, which indicate shifts in the time series resulting from sudden increases or decreases, are represented by red dashed lines.



Regressors where then use to try and acquire more satisfactory outcomes (See Table 11). Though some proved to be successful in this aspect, such models lose the ability to look into the real future, due to the regressor values being unknown. For further detail, check APPENDIX K

.

Table 11. Evaluation results from the Prophet models using regressors.

	MAE	MSE	RMSE	MAPE	Coverage
Max	15083.138	3688827156	18120.942	1.074	0.358
Min	9584.662	206810243	13390.015	0.479	0.064
Median	12001.617	270584332	15359.974	0.695	0.193
Average	12149.705	327986608	15569.926	0.717	0.185

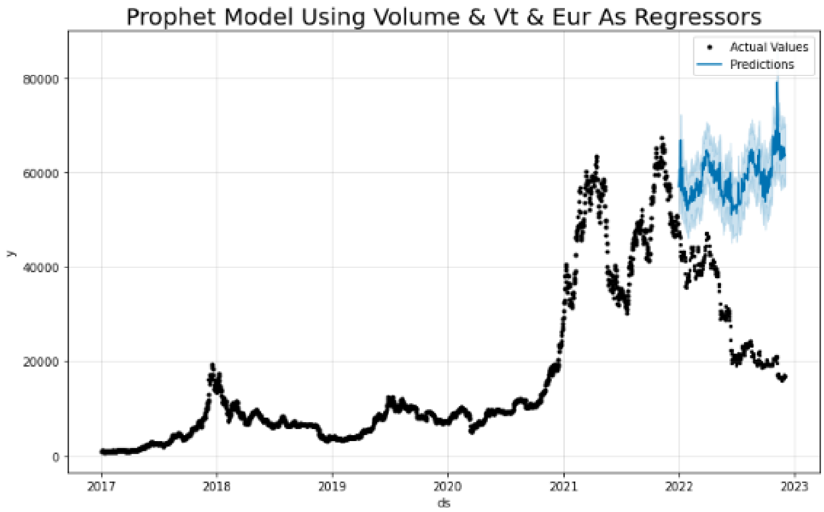
When sorting from smallest to largest the MAE, MSE and RMSE, the first two models are the same, being the one in first place using Volume, VT and Copper as reggressors, while the one in second was using Euro in addition. The third position varies from the model using Volume, VT and Euro, for the one in the first position, to the ones that have in addition Israeli New Shekel and Copper for the following two.

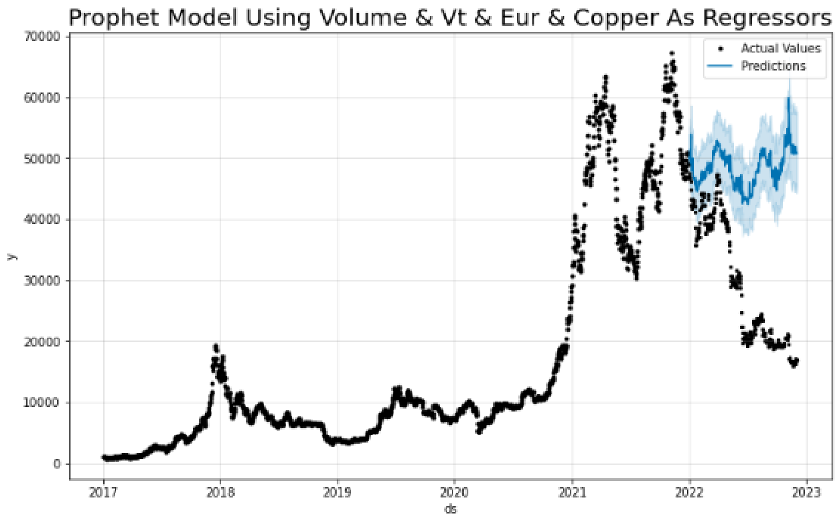
Considering the MAPE metric, the top three were respectfully using the reggressors Volume, VT and Euro, the previous along with Israeli New Shekel, and the last using Volume, VT and Copper. For Coverage, the apparently best model uses Volume, VT, Silvber and Copper as reggressors, while the apparently worst uses all those plus Euro. The middle one uses Volume, VT and Copper. Taking all this into account, with a total of 7 models, it is possible to claim that the most feasible variables are considered by every metric, though not in the same order, and comprise Volume, VT, the commodities Silver and Copper, and the currencies Euro and Israeli New Shekel.

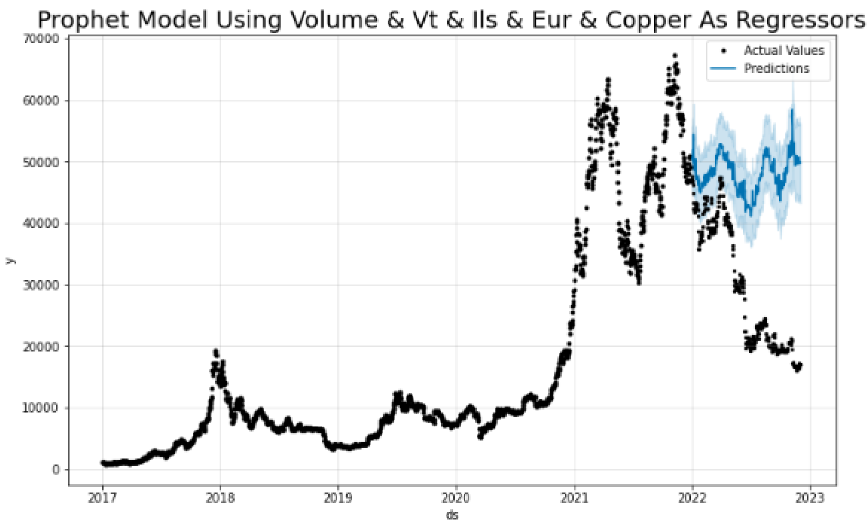
From these models, the ones using three regressors include both Volume and VT, and lastly Euro or Copper. The latter mentioned presents better results apart from the MAPE metric, though none are significantly different. The respective plots also resemble each other and show growing tendency with sudden ups and downs.

The ones using four regressors all include the variables Volume and VT. The missing variables comprise Euro and Copper, Israeli New Shekel and Euro, and Silver and Copper. In this case the second one is better than the first in all aspects except from the MAPE metric and than the third apart from the MAPE and Coverage metrics. The first is also better than the third one except for when considering the MAPE and Coverage metrics.

Figure 15. Plots of Prophet model's predictions against the test set using regressors.







Looking at the curves (See Figure 15), though there is still a growing tendency, it is more evident in the first case mentioned, being the remaining two plots closer to reality and predicting that next peak with more accuracy. On to the ones resorting to 5 regressors, both include the variables Volume, VT, Euro and Copper, differencing alone on using Israeli New Shekel or Silver. Here the first mentioned appears better in terms of the metrics except for the MAPE and Coverage results. The curves also look identical.

Globally speaking there seems to be no tendency between the number of regressors use, but there is a clear pattern in the evaluations, since MAPE seems to always go against the majority of the results. This phenomenom suggest that though such models may be predicitng better for the majority of the time series, for the times the forecasts are not as accurate, there is quite a high percentage of error. This said, it is possible that those models are not positively responding to outliers. Though only often, the same phenomenom happens with Coverage, though this is more likely due to the lack of data and variability representation.

5. CONCLUSIONS

The Bitcoin time series is extremely volatile as it is influenced by many external factors, not only hard to detect, but mostly to keep track and feed predictive models. Due to its nature and Bitcoin halving, though it may reach stability in the distant future, only if it starts to so some signs of seasonality will it be possible to make more accurate predictions.

The variables of study considered to have the most potential to be used in the models fitting were the volume of Bitcoin, the VT index, the currencies Israeli New Shekel and Euro, and the commodities gold and copper.

Regarding the models, though nowadays many different models are used to forecast, most are not prepared to make accurate predictions, nevertheless in the long-time future. Only Prophet fit in the previous category, and had yet many shortcomings, since it was only capable to do so when not considering other variables apart from Bitcoin itself. The use of regressors proved to be promising, but it was only possible to make predictions for an already known future. The RNN model with LSTM layers seemed promising, but only when predicting one day into the real future. Therefore, it is not tangible at present to create predictive models to forecast the price of Bitcoin that would function as support for decision-making over investments, especially in the long term and at a large scale.

Other limitations include computer memory constraints, as well as some models, mostly the RNN with LSTM layers being extremely time consuming when running.

A future recommendation would be the implementation of a hybrid LSTM-NP, which integrates the two types of models that performed better in predicting this time series. By mitigating each other's noise, as well as taking advantage of the combination of their strong points, such a model could potentially lead to better results.

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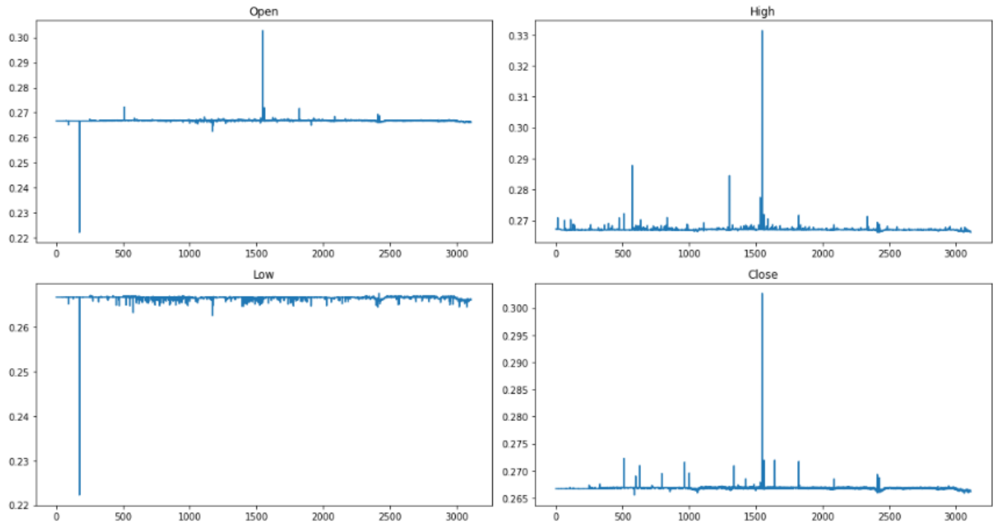
APPENDIX A

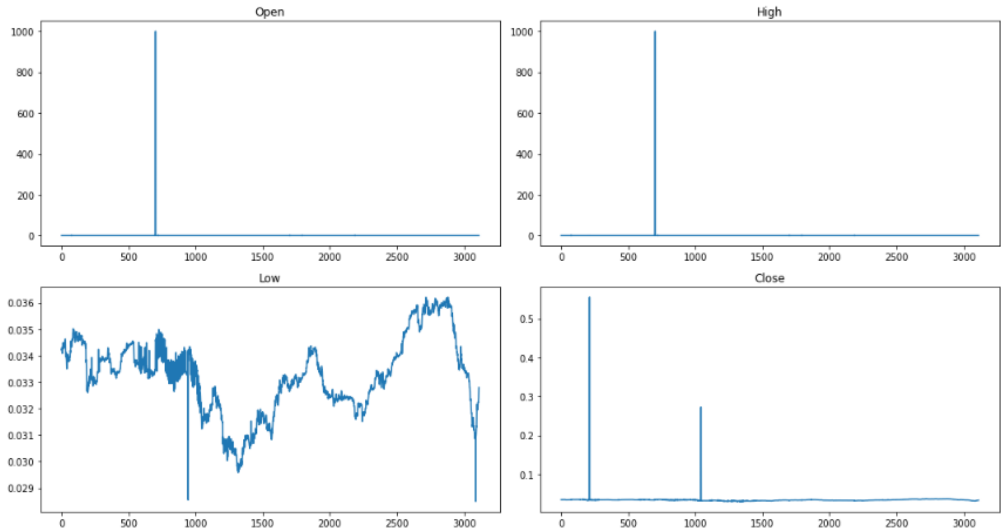
Variable Nature	Variable of Study	Source Name	Platform
Cryptocurrency	Bitcoin	Bitcoin/USD (BTC-USD)	Yahoo Finance
Fiat Currency	Argentine Peso	ARS/USD (ARSUSD=X)	
	Australian Dollar	AUD/USD (AUDUSD=X)	
	Brazilian Real	BRL/USD (BRLUSD=X)	
	Canadian Dollar	CAD/USD (CADUSD=X)	
	Central African CFA Franc	XAF/USD (XAFUSD=X)	
	Danish Krone	DKK/USD (DKKUSD=X)	
	El Salvador Colon	SVC/USD (SVCUSD=X)	
	Euro	EUR/USD (EURUSD=X)	
	Indonesian Rupia	IDR/USD (IDRUSD=X)	
	Israeli New Shekel	ILS/USD (ILSUSD=X)	
	Japanese Yen	JPY/USD (JPYUSD=X)	
	Malaysian Ringgit	MYR/USD (MYRUSD=X)	
	Mexican Peso	MXN/USD (MXNUSD=X)	
	Moroccan Dirham	MAD/USD (MADUSD=X)	
	New Taiwan Dollar	TWD/USD (TWDUSD=X)	
	Nigerian Naira	NGN/USD (NGNUSD=X)	
	Philippine Peso	PHP/USD (PHPUSD=X)	
	Pound Sterling	GBP/USD (GBPUSD=X)	
	Romanian Leu	RON/USD (RONUSD=X)	
	Russian Ruble	RUB/USD (RUBUSD=X)	
	Saudi Riyal	SAR/USD (SARUSD=X)	
	Singapore Dollar	SGD/USD (SGDUSD=X)	
	South African Ran	ZAR/USD (ZARUSD=X)	
	South Korean Won	KRW/USD (KRWUSD=X)	
	Swedish Krona	SEK/USD (SEKUSD=X)	
	Thai Baht	THB/USD (THBUSD=X)	
	Turkish Lira	TRY/USD (TRYUSD=X)	
Index	VOO Index	Vanguard 500 Index Fund (VOO)	
	VT Index	Vanguard Total World Stock Index Fund (VT)	
Commodity	Copper	Copper Prices - 45 Year Historical Chart	Macrotrends
	Gold	Gold Prices - 100 Year Historical Chart	
	Silver	Silver Prices - 100 Year Historical Chart	

APPENDIX B

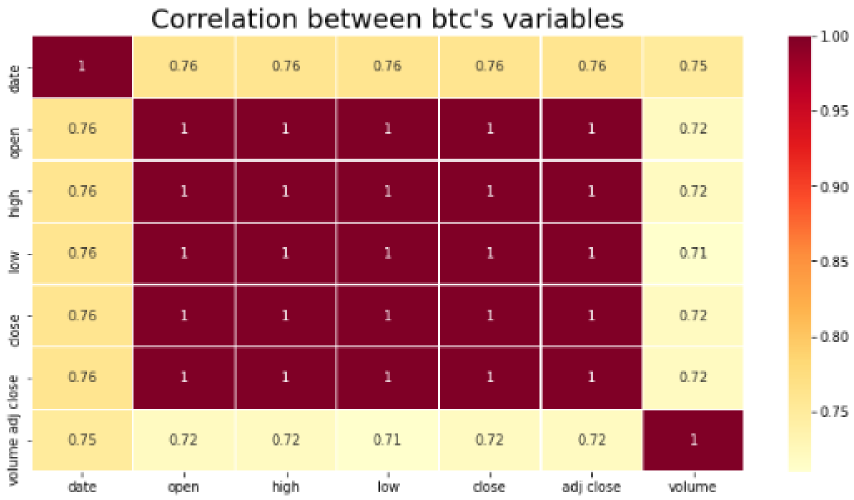
Saudi Riyal time series



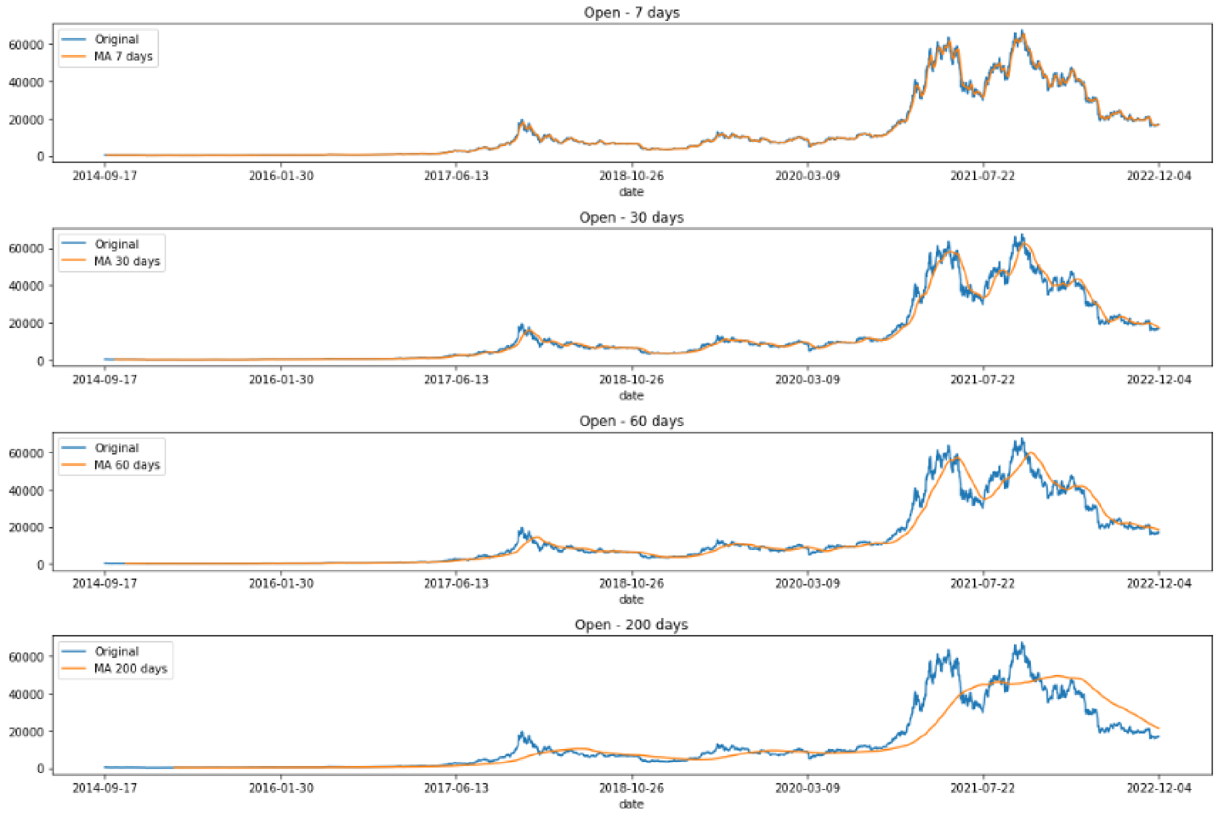
New Taiwan Dollar time series



APPENDIX C

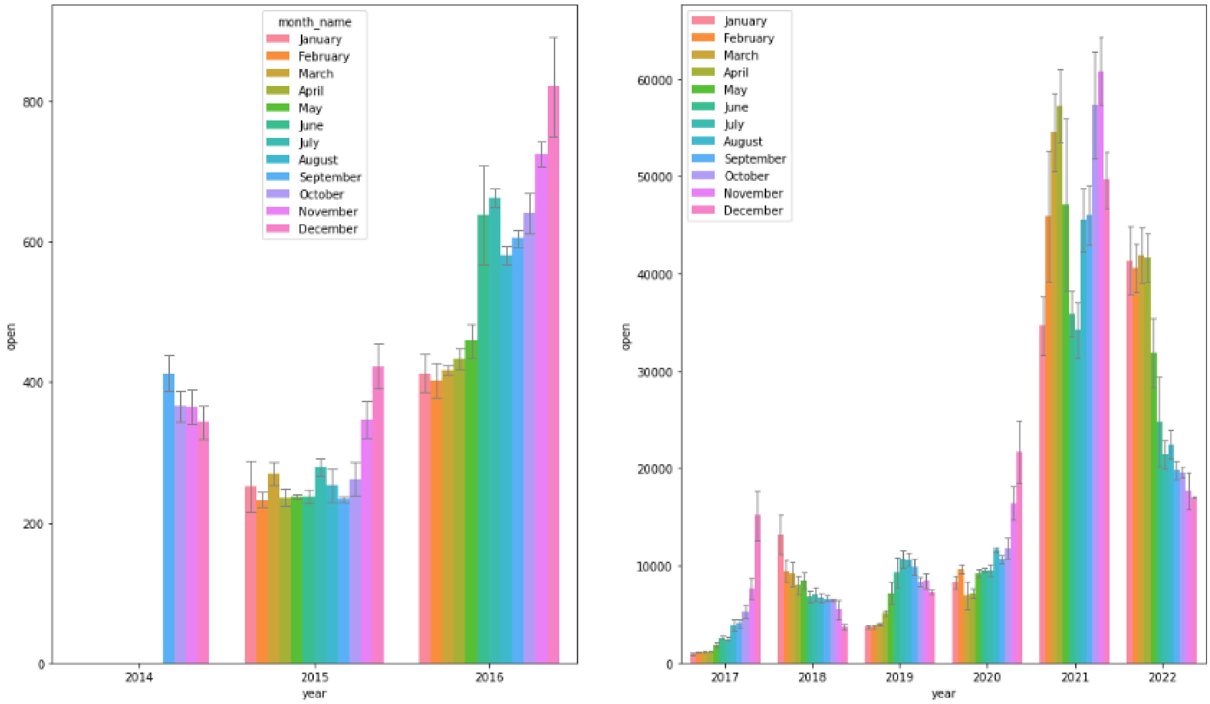


APPENDIX D

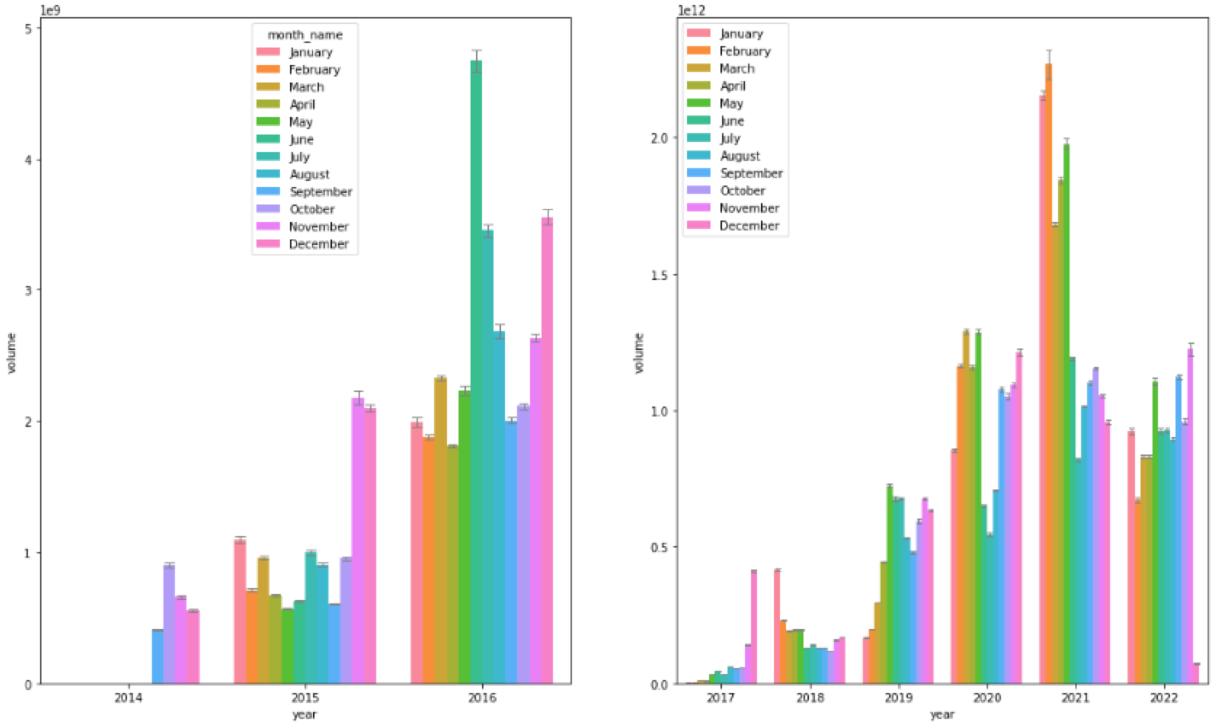


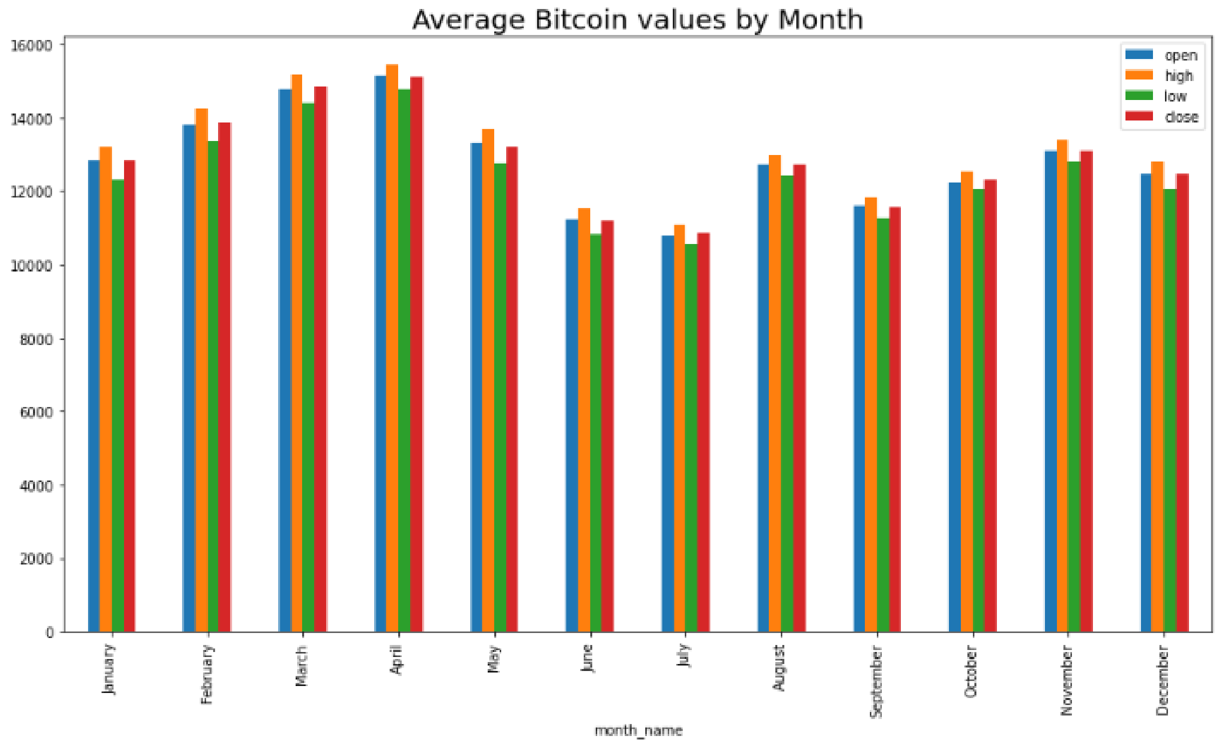
APPENDIX E

Average Bitcoin Open Value by Month through Time

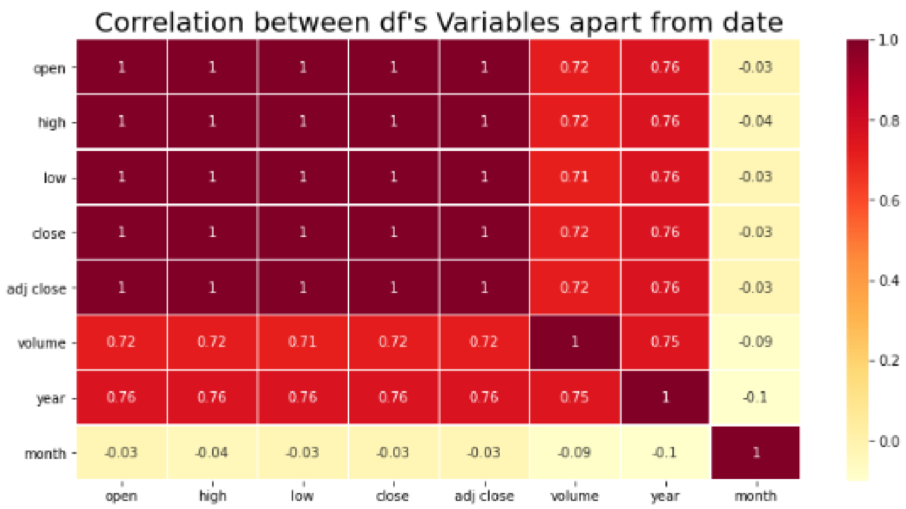


Sum Bitcoin Volume Value by Month through Time



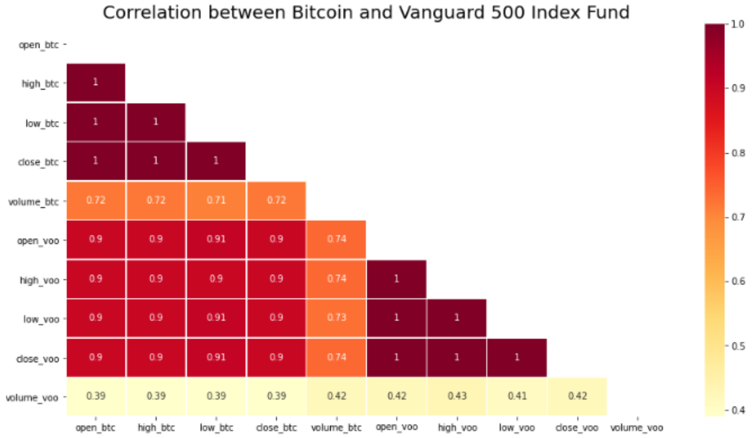

Average Bitcoin values by Month
16000
14000
12000
10000
8000
6000
4000
2000
0
open
high
low
close
January
February
March
April
May
June
July
August
September
October
November
December
month_name

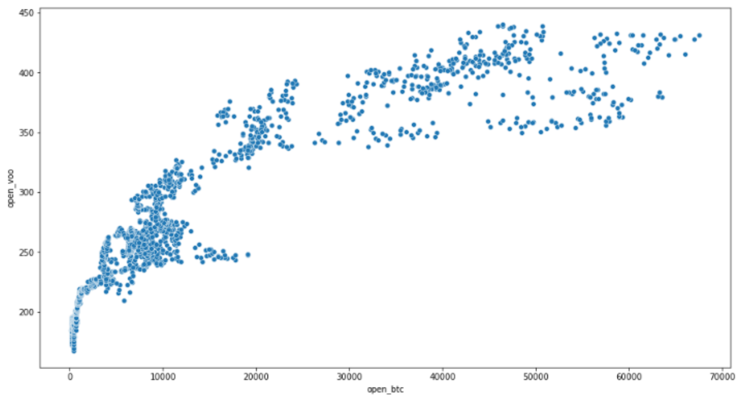
APPENDIX F


Correlation between df's Variables apart from date
open 1 1 1 1 1 0.72 0.76 -0.03
high 1 1 1 1 1 0.72 0.76 -0.04
low 1 1 1 1 1 0.71 0.76 -0.03
close 1 1 1 1 1 0.72 0.76 -0.03
adj close 1 1 1 1 1 0.72 0.76 -0.03
volume 0.72 0.72 0.71 0.72 0.72 1 0.75 -0.09
year 0.76 0.76 0.76 0.76 0.76 0.75 1 -0.1
month -0.03 -0.04 -0.03 -0.03 -0.03 -0.09 -0.1 1
open
high
low
close
adj close
volume
year
month
1.0
0.8
0.6
0.4
0.2
0.0

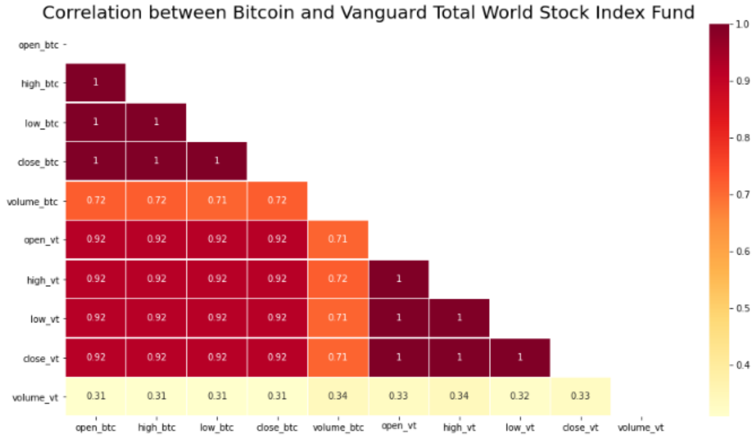
APPENDIX G

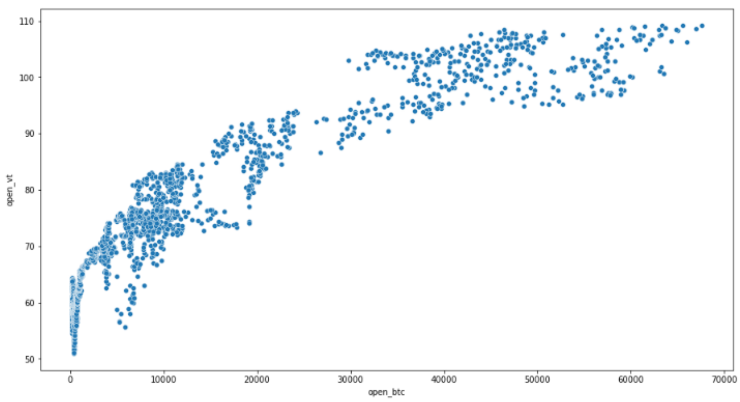
Correlation between Bitcoin and Vanguard 500 Index Fund

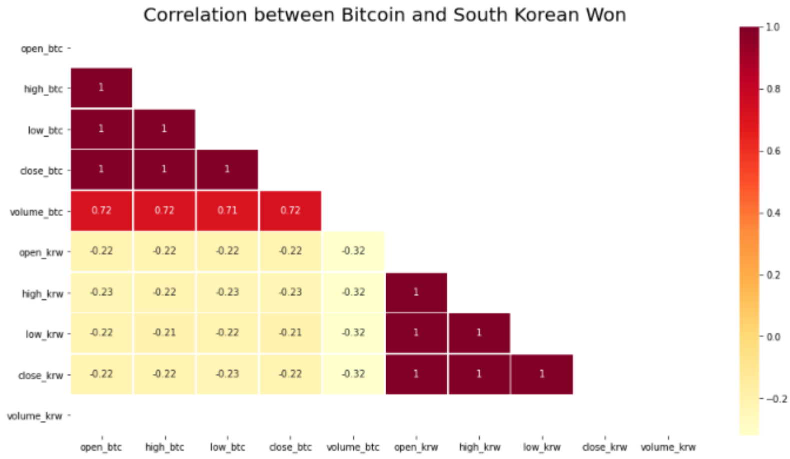


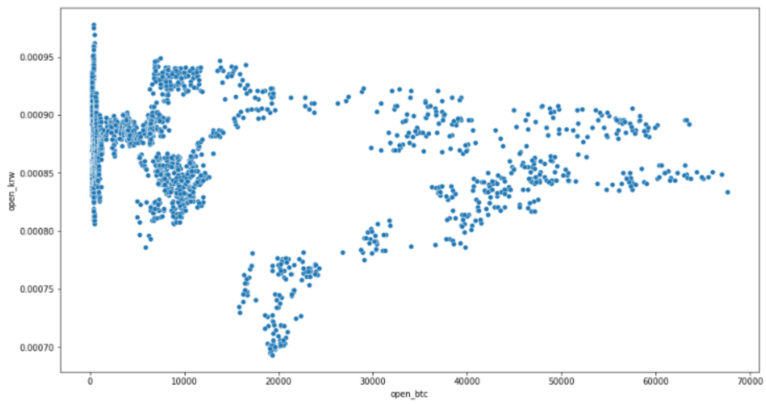


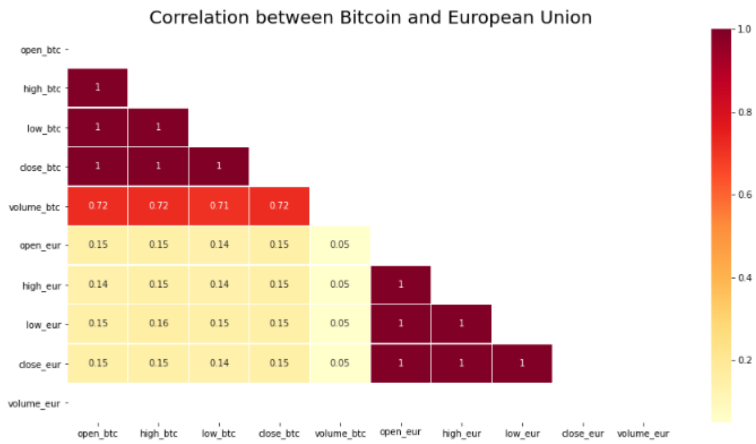
Correlation between Bitcoin and Vanguard Total World Stock Index Fund

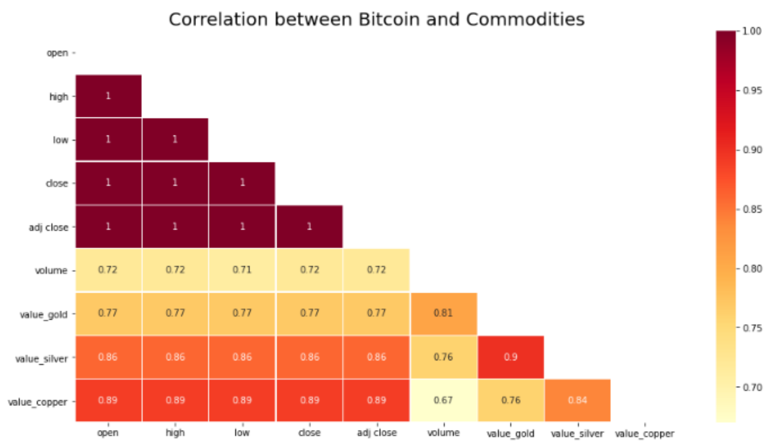


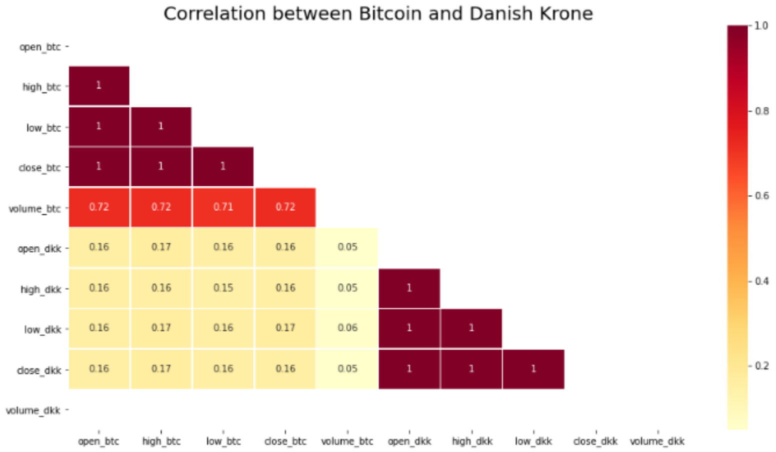


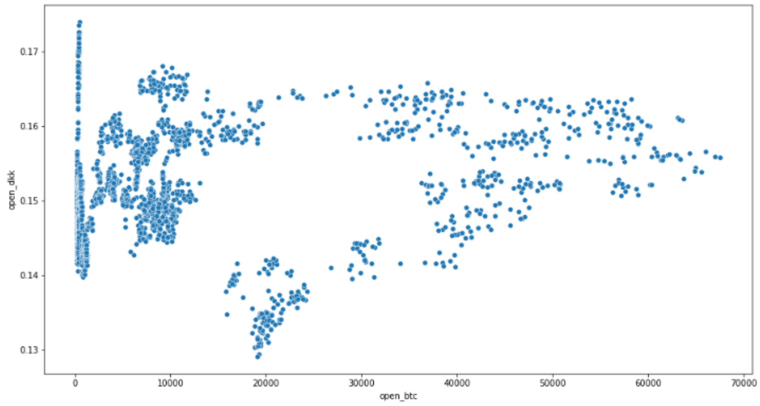

Correlation between Bitcoin and South Korean Won
open_btc
high_btc
low_btc
close_btc
volume_btc
open_krw
high_krw
low_krw
close_krw
volume_krw

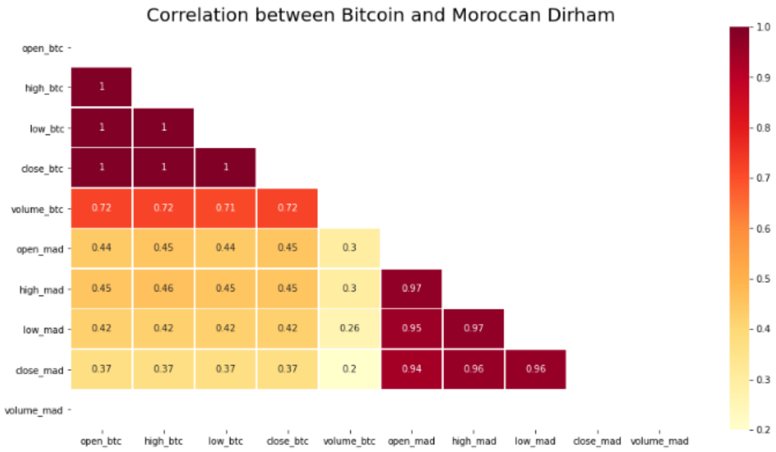

open_krw
open_btc

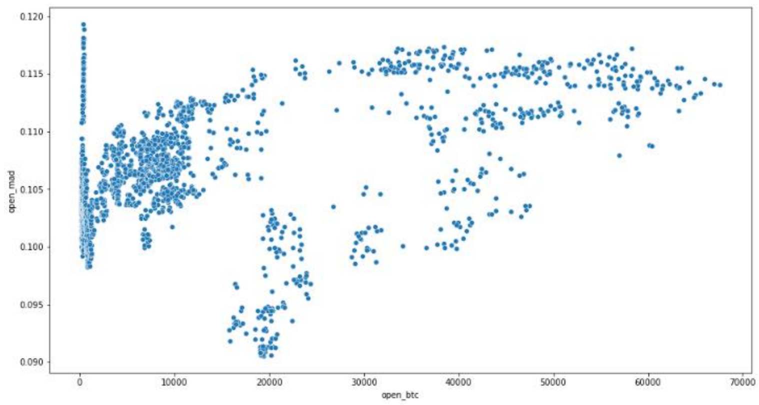

Correlation between Bitcoin and European Union
open_btc
high_btc
low_btc
close_btc
volume_btc
open_eur
high_eur
low_eur
close_eur
volume_eur

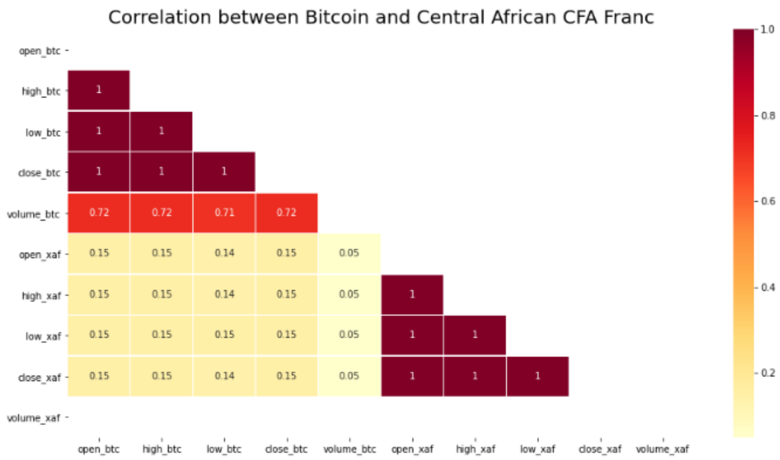

Correlation between Bitcoin and Commodities
open
high
low
close
adj close
volume
value_gold
value_silver
value_copper

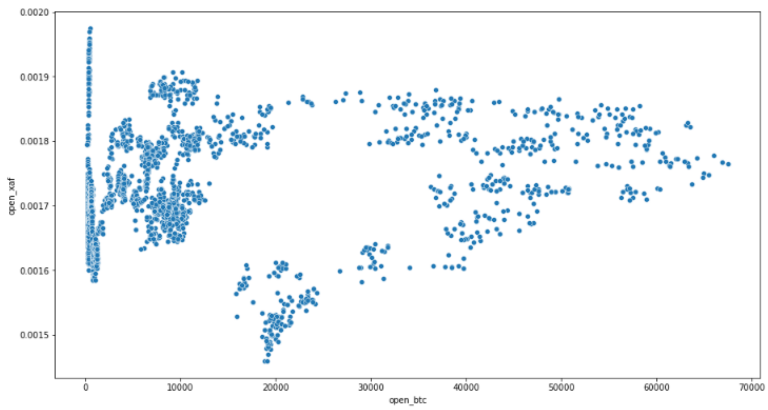

Correlation between Bitcoin and Danish Krone
open_btc
high_btc
low_btc
close_btc
volume_btc
open_dkk
high_dkk
low_dkk
close_dkk
volume_dkk


open_dkk
open_btc


Correlation between Bitcoin and Moroccan Dirham
open_btc
high_btc
low_btc
close_btc
volume_btc
open_mad
high_mad
low_mad
close_mad
volume_mad


open_mad
open_btc


Correlation between Bitcoin and Central African CFA Franc
open_btc
high_btc
low_btc
close_btc
volume_btc
open_xaf
high_xaf
low_xaf
close_xaf
volume_xaf
1.0
0.8
0.6
0.4
0.2


open_xaf
open_btc
0.0020
0.0019
0.0018
0.0017
0.0016
0.0015
0
10000
20000
30000
40000
50000
60000
70000

APPENDIX H

Nb. Additional Input Variables in the Combination	Variables	Nb. of Combinations
-	['value_btc']	1
1	['value_btc', 'volume'] ['value_btc', 'value_vt'] ['value_btc', 'value_ils'] ['value_btc', 'value_eur'] ['value_btc', 'value_silver'] ['value_btc', 'value_copper']	6
2	['value_btc', 'volume', 'value_vt'] ['value_btc', 'volume', 'value_ils'] ['value_btc', 'volume', 'value_eur'] ['value_btc', 'volume', 'value_silver'] ['value_btc', 'volume', 'value_copper'] ['value_btc', 'value_vt', 'value_ils'] ['value_btc', 'value_vt', 'value_eur'] ['value_btc', 'value_vt', 'value_silver'] ['value_btc', 'value_vt', 'value_copper'] ['value_btc', 'value_ils', 'value_eur'] ['value_btc', 'value_ils', 'value_silver'] ['value_btc', 'value_ils', 'value_copper'] ['value_btc', 'value_eur', 'value_silver'] ['value_btc', 'value_eur', 'value_copper'] ['value_btc', 'value_silver', 'value_copper']	15
3	['value_btc', 'volume', 'value_vt', 'value_ils'] ['value_btc', 'volume', 'value_vt', 'value_eur'] ['value_btc', 'volume', 'value_vt', 'value_silver'] ['value_btc', 'volume', 'value_vt', 'value_copper'] ['value_btc', 'volume', 'value_ils', 'value_eur'] ['value_btc', 'volume', 'value_ils', 'value_silver'] ['value_btc', 'volume', 'value_ils', 'value_copper'] ['value_btc', 'volume', 'value_eur', 'value_silver'] ['value_btc', 'volume', 'value_eur', 'value_copper'] ['value_btc', 'volume', 'value_silver', 'value_copper'] ['value_btc', 'value_vt', 'value_ils', 'value_eur'] ['value_btc', 'value_vt', 'value_ils', 'value_silver'] ['value_btc', 'value_vt', 'value_ils', 'value_copper'] ['value_btc', 'value_vt', 'value_eur', 'value_silver'] ['value_btc', 'value_vt', 'value_eur', 'value_copper'] ['value_btc', 'value_vt', 'value_silver', 'value_copper'] ['value_btc', 'value_ils', 'value_eur', 'value_silver'] ['value_btc', 'value_ils', 'value_eur', 'value_copper'] ['value_btc', 'value_ils', 'value_silver', 'value_copper'] ['value_btc', 'value_eur', 'value_silver', 'value_copper']	20
4	['value_btc', 'volume', 'value_vt', 'value_ils', 'value_eur'] ['value_btc', 'volume', 'value_vt', 'value_ils', 'value_silver'] ['value_btc', 'volume', 'value_vt', 'value_ils', 'value_copper'] ['value_btc', 'volume', 'value_vt', 'value_eur', 'value_silver'] ['value_btc', 'volume', 'value_vt', 'value_eur', 'value_copper'] ['value_btc', 'volume', 'value_vt', 'value_silver', 'value_copper'] ['value_btc', 'volume', 'value_ils', 'value_eur', 'value_silver'] ['value_btc', 'volume', 'value_ils', 'value_eur', 'value_copper'] ['value_btc', 'volume', 'value_ils', 'value_silver', 'value_copper'] ['value_btc', 'volume', 'value_eur', 'value_silver', 'value_copper'] ['value_btc', 'value_vt', 'value_ils', 'value_eur', 'value_silver'] ['value_btc', 'value_vt', 'value_ils', 'value_eur', 'value_copper'] ['value_btc', 'value_vt', 'value_ils', 'value_silver', 'value_copper'] ['value_btc', 'value_vt', 'value_eur', 'value_silver', 'value_copper'] ['value_btc', 'value_ils', 'value_eur', 'value_silver', 'value_copper']	15
5	['value_btc', 'volume', 'value_vt', 'value_ils', 'value_eur', 'value_silver'] ['value_btc', 'volume', 'value_vt', 'value_ils', 'value_eur', 'value_copper'] ['value_btc', 'volume', 'value_vt', 'value_ils', 'value_silver', 'value_copper'] ['value_btc', 'volume', 'value_vt', 'value_eur', 'value_silver', 'value_copper'] ['value_btc', 'volume', 'value_ils', 'value_eur', 'value_silver', 'value_copper'] ['value_btc', 'value_vt', 'value_ils', 'value_eur', 'value_silver', 'value_copper']	6
6	['value_btc', 'volume', 'value_vt', 'value_ils', 'value_eur', 'value_silver', 'value_copper']	1

APPENDIX I

Combination	Nobs	Log Likelihood	AIC	BIC	HQIC	FPE	Det (Omega_mle)
Bitcoin and Volume	1795	-57215.6	58.2101	58.5834	58.3479	1.91E+25	1.78E+25
Bitcoin and VT	1796	-14864.7	11.0088	11.3697	11.1421	60407	56625.5
Bitcoin and Israeli New Shekel	1805	3790.38	-1.38503	-1.13524	-1.29284	0.25032	0.239324
Bitcoin and Euro	1801	-6105.24	1.21291	1.51198	1.3233	3.36335	3.18754
Bitcoin and Silver	1810	-12886.8	8.63233	8.82077	8.70187	5610.18	5422.83
Bitcoin and Copper	1796	-10022.1	5.61612	5.97704	5.74937	274.835	257.63
Bitcoin, Volume and VT	1795	-58430.3	56.894	57.7294	57.2024	5.12E+24	4.41E+24
Bitcoin, Volume, and Israeli New Shekel	1818	-48218	44.6041	44.804	44.6778	2.35E+19	2.27E+19
Bitcoin, Volume and Euro	1807	-50136.9	47.1609	47.6631	47.3462	3.03E+20	2.77E+20
Bitcoin, Volume and Silver	1795	-56291.7	54.5111	55.3465	54.8195	4.72E+23	4.07E+23
Bitcoin, Volume and Copper	1795	-53515	51.4173	52.2527	51.7258	2.14E+22	1.84E+22
Bitcoin, VT, and Israeli New Shekel	1805	-4874.78	-2.90945	-2.352	-2.7037	0.0545102	0.0493372
Bitcoin, VT, and Euro	1815	-7464.3	-0.186033	0.095982	-0.081974	0.830255	0.789126
Bitcoin, VT, and Silver	1815	-14241.2	7.28164	7.56366	7.3857	1453.39	1381.39
Bitcoin, VT, and Copper	1810	-11445.6	4.28591	4.70533	4.44069	72.6709	67.4003
Bitcoin, Israeli New Shekel and Euro	1815	3797.91	-12.5962	-12.3142	-12.4921	3.38E-06	3.22E-06
Bitcoin, Israeli New Shekel and Silver	1810	-2947.19	-5.10458	-4.68516	-4.9498	0.00606909	0.00562892
Bitcoin, Israeli New Shekel and Copper	1804	-146.259	-8.13862	-7.55349	-7.92265	0.00029207	0.000263063
Bitcoin, Euro, and Silver	1815	-5342.97	-2.52358	-2.24156	-2.41952	0.0801731	0.0762015
Bitcoin, Euro, and Copper	1814	-2608.95	-5.52471	-5.21527	-5.41053	0.00398706	0.00377102
Bitcoin, Silver, and Copper	1818	-8844.38	1.28877	1.48864	1.36251	3.62833	3.49973
Bitcoin, Volume, VT, and Israeli New Shekel	1814	-49192.8	43.0838	43.6298	43.2853	5.14E+18	4.66E+18

Bitcoin, Volume, VT, and Euro	1815	-51679.4	45.7762	46.2735	45.9597	7.59E+19	6.94E+19
Bitcoin, Volume, VT, and Silver	1815	-58438.5	53.2243	53.7216	53.4078	1.30E+23	1.19E+23
Bitcoin, Volume, VT, Copper	1795	-54692.4	50.1264	51.6074	50.6732	5.89E+21	4.54E+21
Bitcoin, Volume, Israeli New Shekel, and Euro	1819	-40617.3	33.4173	33.72	33.529	3.26E+14	3.08E+14
Bitcoin, Volume, Israeli New Shekel, and Silver	1815	-47216.3	40.8582	41.3555	41.0417	5.55E+17	5.08E+17
Bitcoin, Volume, Israeli New Shekel, and Copper	1809	-44285.4	37.8972	38.6877	38.1889	2.87E+16	2.50E+16
Bitcoin, Volume, Euro, and Silver	1818	-49678.6	43.4281	43.7793	43.5577	7.25E+18	6.81E+18
Bitcoin, Volume, Euro, and Copper	1804	-46351.8	40.4132	41.4494	40.7957	3.56E+17	2.96E+17
Bitcoin, Volume, Silver, and Copper	1810	-52772.6	47.2303	47.9719	47.504	3.25E+20	2.85E+20
Bitcoin, VT, Israeli New Shekel and Euro	1815	2689.54	-14.1345	-13.6372	-13.951	7.27E-07	6.65E-07
Bitcoin, VT, Israeli New Shekel and Silver	1810	-4041.66	-6.61598	-5.87439	-6.34231	0.00133894	0.00117269
Bitcoin, VT, Israeli New Shekel and Copper	1810	-1296.86	-9.6489	-8.90732	-9.37523	6.45E-05	5.65E-05
Bitcoin, VT, Euro, and Silver	1815	-6588.24	-3.91102	-3.4137	-3.72752	0.0200207	0.0183094
Bitcoin, VT, Euro, and Copper	1815	-3868.17	-6.90835	-6.41103	-6.72485	0.00099944	0.000914007
Bitcoin, VT, Silver, and Copper	1818	-10158.9	-0.04802	0.303265	0.081587 7	0.953125	0.894659
Bitcoin, Israeli New Shekel, Euro, and Silver	1815	4675.57	-16.3229	-15.8256	-16.1394	8.15E-08	7.45E-08
Bitcoin, Israeli New Shekel, Euro, and Copper	1810	7475.66	-19.3423	-18.6007	-19.0686	3.98E-09	3.49E-09
Bitcoin, Israeli New Shekel, Silver, and Copper	1818	1110.41	-12.4455	-12.0942	-12.3159	3.94E-06	3.69E-06
Bitcoin, Euro, Silver, and Copper	1818	-1220.91	-9.88076	-9.52947	-9.75115	5.12E-05	4.80E-05

Bitcoin, Volume, VT, Israeli New Shekel, and Euro	1818	-41741.8	31.9292	32.4743	32.1303	7.36E+13	6.67E+13
Bitcoin, Volume, VT, Israeli New Shekel, and Silver	1818	-48506.8	39.3714	39.9165	39.5726	1.26E+17	1.14E+17
Bitcoin, Volume, VT, Israeli New Shekel, and Copper	1806	-45135.4	36.326	37.7874	36.8654	5.98E+15	4.61E+15
Bitcoin, Volume, VT, Euro, and Silver	1815	-50780.1	42.0476	42.8209	42.3329	1.82E+18	1.59E+18
Bitcoin, Volume, VT, Euro, and Copper	1815	-48057.8	39.0478	39.8211	39.3332	9.08E+16	7.91E+16
Bitcoin, Volume, VT, Silver, and Copper	1818	-54435.6	45.8938	46.4389	46.0949	8.54E+19	7.74E+19
Bitcoin, Volume, Israeli New Shekel, Euro, and Silver	1816	-39614.7	29.6924	30.3896	29.9496	7.86E+12	6.93E+12
Bitcoin, Volume, Israeli New Shekel, Euro, and Copper	1818	-36987.7	26.6991	27.2442	26.9002	3.94E+11	3.57E+11
Bitcoin, Volume, Israeli New Shekel, Silver, and Copper	1817	-43193.8	33.5804	34.2015	33.8095	3.84E+14	3.43E+14
Bitcoin, Volume, Euro, Silver, and Copper	1818	-45510.7	36.0754	36.6205	36.2765	4.65E+15	4.21E+15
Bitcoin, VT, Israeli New Shekel, Euro, and Silver	1815	3570.84	-17.8432	-17.0699	-17.5579	1.78E-08	1.55E-08
Bitcoin, VT, Israeli New Shekel, Euro, and Copper	1810	6424.91	-20.8688	-19.7139	-20.4426	8.65E-10	7.04E-10
Bitcoin, VT, Israeli New Shekel, Silver, and Copper	1818	-49.4957	-13.9369	-13.3918	-13.7358	8.86E-07	8.03E-07
Bitcoin, VT, Euro, Silver, and Copper	1818	-2495.22	-11.2463	-10.7012	-11.0452	1.31E-05	1.18E-05
Bitcoin, Israeli New Shekel, Euro, Silver, and Copper	1818	8796.78	-23.6688	-23.1237	-23.4677	5.26E-11	4.77E-11
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Silver	1818	-40841.8	28.187	28.9684	28.4753	1.74E+12	1.52E+12
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Copper	1814	-37885.5	25.186	26.4056	25.6361	8.67E+10	6.98E+10

Bitcoin, Volume, VT, Israeli New Shekel, Silver, and Copper	1819	-44441.1	32.08	32.752	32.328	8.55E+13	7.58E+13
Bitcoin, Volume, VT, Euro, Silver, and Copper	1818	-46770.7	34.7094	35.4907	34.9977	1.19E+15	1.03E+15
Bitcoin, Volume, Israeli New Shekel, Euro, Silver, and Copper	1821	-35701.1	22.3479	22.8016	22.5153	5.08E+09	4.68E+09
Bitcoin, VT, Israeli New Shekel, Euro, Silver, and Copper	1818	7668.03	-25.1791	-24.3978	-24.8908	1.16E-11	1.01E-11
Bitcoin, Volume, VT, Israeli New Shekel, Euro, Silver, and Copper	1821	-36884	20.8675	21.4814	21.0939	1.16E+09	1.03E+09

APPENDIX J

Combination	N. Prediction Days	MAE	MSE	RMSE	R2
Bitcoin	7	1340.838	3870963	1967.476	0.960
	30	1209.760	2935875	1713.439	0.969
	60	1076.405	2588640	1608.925	0.969
	200	675.975	930916	964.840	0.812
Bitcoin and Volume	7	1289.027	3562985	1887.587	0.963
	30	1172.605	2818969	1678.978	0.970
	60	1057.219	2348128	1532.360	0.972
	200	908.606	1308527	1143.908	0.736
Bitcoin and VT	7	1329.678	3807995	1951.408	0.961
	30	1257.636	3351814	1830.796	0.964
	60	1140.851	2901528	1703.387	0.965
	200	809.670	1114809	1055.845	0.775
Bitcoin and Israeli New Shekel	7	1333.835	3779199	1944.016	0.961
	30	1194.415	3045853	1745.237	0.968
	60	1118.824	2775273	1665.915	0.967
	200	828.733	1124186	1060.277	0.773
Bitcoin and Euro	7	1404.966	4216762	2053.476	0.957
	30	1281.464	3382715	1839.216	0.964

	60	1289.225	3531412	1879.205	0.958
	200	936.544	1348420	1161.215	0.728
Bitcoin and Silver	7	1346.532	3902502	1975.475	0.960
	30	1176.061	2993080	1730.052	0.968
	60	1221.926	2854088	1689.405	0.966
	200	788.245	1098278	1047.988	0.778
Bitcoin and Copper	7	1921.652	5831666	2414.884	0.940
	30	1337.800	3497747	1870.227	0.963
	60	1157.825	2727273	1651.446	0.967
	200	964.721	1373022	1171.760	0.723
Bitcoin, Volume and VT	7	1321.931	3750803	1936.699	0.961
	30	1225.567	3119478	1766.204	0.967
	60	1130.991	2762078	1661.950	0.967
	200	947.195	1394575	1180.921	0.718
Bitcoin, Volume, and Israeli New Shekel	7	1328.268	3549336	1883.968	0.964
	30	1218.241	3065338	1750.811	0.967
	60	1115.136	2516321	1586.291	0.970
	200	1085.429	1739665	1318.963	0.649
Bitcoin, Volume and Euro	7	1424.467	4139510	2034.579	0.957
	30	1295.666	3483475	1866.407	0.963
	60	1462.523	4188181	2046.505	0.950
	200	794.695	1196530	1093.860	0.758
Bitcoin, Volume and Silver	7	1374.561	4060718	2015.122	0.958
	30	1178.239	2890114	1700.034	0.969
	60	1122.060	2786173	1669.183	0.967
	200	751.439	1003518	1001.758	0.797
Bitcoin, Volume and Copper	7	1611.769	4762091	2182.222	0.951
	30	1227.383	2951157	1717.893	0.969
	60	1147.034	2725607	1650.941	0.967
	200	1004.135	1491317	1221.195	0.699
Bitcoin, VT, and Israeli New Shekel	7	1333.663	3715433	1927.546	0.962
	30	1273.200	3374787	1837.059	0.964

	60	1382.707	3296910	1815.739	0.961
	200	958.514	1411411	1188.028	0.714
Bitcoin, VT, and Euro	7	1534.877	4194491	2048.046	0.957
	30	1393.783	3939584	1984.838	0.958
	60	1524.882	3757473	1938.420	0.955
	200	1189.082	2002513	1415.102	0.595
Bitcoin, VT, and Silver	7	1300.299	3692559	1921.603	0.962
	30	1291.561	3640876	1908.108	0.961
	60	1177.799	3075369	1753.673	0.963
	200	1092.031	1716716	1310.235	0.653
Bitcoin, VT, and Copper	7	1637.355	4729924	2174.839	0.951
	30	1451.522	3927636	1981.826	0.958
	60	1400.660	3776483	943.318	0.955
	200	1496.625	3309426	1819.183	0.332
Bitcoin, Israeli New Shekel and Euro	7	1552.830	4161285	2039.923	0.957
	30	1401.922	4095345	2023.696	0.956
	60	1464.024	3835564	1958.460	0.954
	200	1126.893	1906219	1380.659	0.615
Bitcoin, Israeli New Shekel and Silver	7	1303.237	3571663	1889.884	0.963
	30	1213.369	3131456	1769.592	0.967
	60	1150.701	3044990	1744.990	0.964
	200	1160.244	1840274	1356.567	0.628
Bitcoin, Israeli New Shekel and Copper	7	1564.359	4659149	2158.506	0.952
	30	1387.910	3598895	1897.075	0.962
	60	1354.042	3361649	1833.480	0.960
	200	1739.449	3789486	1946.660	0.235
Bitcoin, Euro, and Silver	7	1739.791	4709588	2170.159	0.952
	30	1609.258	4864304	2205.517	0.948
	60	1210.482	3340752	1827.773	0.960
	200	868.069	1306290	1142.930	0.736
Bitcoin, Euro, and Copper	7	2799.187	10514690	3242.636	0.892
	30	4197.208	21856739	4675.119	0.767

	60	3056.158	12131332	3483.006	0.855
	200	3859.273	16385890	4047.949	-2.310
Bitcoin, Silver, and Copper	7	1542.389	4544546	2131.794	0.953
	30	1308.650	342606	1850.962	0.963
	60	1185.926	3061857	1749.816	0.963
	200	922.543	1352153	1162.821	0.727
Bitcoin, Volume, VT, and Israeli New Shekel	7	1380.450	3704864	1924.802	0.962
	30	1224.951	3060353	1749.386	0.967
	60	1179.215	2945203	1716.159	0.965
	200	1084.485	1767684	1329.543	0.643
Bitcoin, Volume, VT, and Euro	7	1562.472	4124931	2030.993	0.958
	30	1612.178	4823037	2196.141	0.949
	60	1249.269	2977804	1725.632	0.964
	200	1181.443	1976897	1406.022	0.601
Bitcoin, Volume, VT, and Silver	7	1319.928	3726242	1930.348	0.962
	30	1476.450	4158908	2039.340	0.956
	60	1141.448	2959614	1720.353	0.965
	200	753.590	939801	969.434	0.810
Bitcoin, Volume, VT, and Copper	7	1716.991	5047604	2246.687	0.948
	30	2262.969	7341105	2709.447	0.922
	60	1275.005	3284011	1812.184	0.961
	200	823.531	1140335	1067.865	0.770
Bitcoin, Volume, Israeli New Shekel, and Euro	7	1619.889	4333842	2081.788	0.955
	30	1394.479	3887285	1971.620	0.959
	60	1348.823	3524406	1877.340	0.958
	200	2387.900	6594412	2567.959	-0.332
Bitcoin, Volume, Israeli New Shekel, and Silver	7	1347.356	3899174	1974.633	0.960
	30	1492.569	4236978	2058.392	0.955
	60	1094.355	2717583	1648.509	0.968
	200	748.797	993651	996.820	0.799
Bitcoin, Volume, Israeli New Shekel, and Copper	7	1924.006	5730599	2393.867	0.941
	30	1452.647	3798449	1948.961	0.959

	60	1239.108	2972351	1724.051	0.965
	200	1009.348	1635152	1278.731	0.670
Bitcoin, Volume, Euro, and Silver	7	1642.750	4457082	2111.180	0.954
	30	1883.764	6114428	2472.737	0.935
	60	1552.556	4559466	2135.291	0.946
	200	881.656	1266320	1125.309	0.744
Bitcoin, Volume, Euro, and Copper	7	2405.677	8137066	2852.554	0.916
	30	4121.787	20634962	4542.572	0.780
	60	3272.829	13676950	3698.236	0.837
	200	4467.576	21288739	4613.972	-3.300
Bitcoin, Volume, Silver, and Copper	7	1389.657	3911360	1977.716	0.960
	30	1492.901	3958446	1989.584	0.958
	60	1123.340	2735613	1653.969	0.967
	200	1365.817	2497634	1580.390	0.495
Bitcoin, VT, Israeli New Shekel and Euro	7	1854.936	5056561	2248.680	0.948
	30	1561.517	4892150	2211.821	0.948
	60	1774.567	4539968	2130.720	0.946
	200	848.013	1274949	1129.137	0.742
Bitcoin, VT, Israeli New Shekel and Silver	7	1307.900	3754553	1937.667	0.961
	30	1918.119	5826413	2413.796	0.938
	60	1376.467	3646448	1909.568	0.957
	200	2113.156	5430811	2330.410	-0.097
Bitcoin, VT, Israeli New Shekel and Copper	7	1427.556	4217078	2053.552	0.957
	30	1774.521	5090730	2256.265	0.946
	60	1402.886	3903766	1975.795	0.953
	200	925.604	1428735	1195.297	0.711
Bitcoin, VT, Euro, and Silver	7	1554.096	4203390	2050.217	0.957
	30	2079.832	6790494	2605.858	0.928
	60	1270.614	3460505	1860.243	0.959
	200	1059.092	1675910	1294.569	0.661
Bitcoin, VT, Euro, and Copper	7	1953.182	6136049	2477.105	0.937
	30	3839.589	18739990	4328.971	0.800

	60	4009.986	20298775	4505.416	0.758
	200	4375.874	21643848	4652.295	-3.372
Bitcoin, VT, Silver, and Copper	7	1782.058	5184309	2276.908	0.947
	30	1432.679	3905438	1976.218	0.958
	60	1297.278	3581900	1892.591	0.957
	200	1039.756	1767726	1329.559	0.643
Bitcoin, Israeli New Shekel, Euro, and Silver	7	1470.804	4082909	2020.621	0.958
	30	2381.334	8688170	2947.570	0.907
	60	1242.538	3369225	1835.545	0.960
	200	868.558	1379348	1174.456	0.721
Bitcoin, Israeli New Shekel, Euro, and Copper	7	2310.202	7761993	2786.035	0.920
	30	4601.946	25071545	5007.149	0.733
	60	1713.584	5340928	2311.045	0.936
	200	6225.159	41970895	6478.495	-7.478
Bitcoin, Israeli New Shekel, Silver, and Copper	7	1635.228	4716844	2171.830	0.952
	30	1742.357	4945519	2223.852	0.947
	60	1556.946	4040823	2010.180	0.952
	200	1001.336	1751079	1323.283	0.646
Bitcoin, Euro, Silver, and Copper	7	2680.666	9744676	3121.646	0.900
	30	4101.212	20299543	4505.501	0.784
	60	2711.215	9998581	3162.053	0.881
	200	5092.737	27454129	5239.669	-4.546
Bitcoin, Volume, VT, Israeli New Shekel, and Euro	7	1639.079	4348030	2085.193	0.955
	30	1450.231	4328216	2080.437	0.954
	60	1370.393	3441919	1855.241	0.959
	200	2105.853	5265705	2294.712	-0.064
Bitcoin, Volume, VT, Israeli New Shekel, and Silver	7	1417.214	3889079	1972.075	0.960
	30	2013.973	6448932	2539.474	0.931
	60	1207.987	3074920	1753.545	0.963
	200	1330.484	2345736	1531.580	0.526
Bitcoin, Volume, VT, Israeli New Shekel, and Copper	7	1706.122	4943652	2223.433	0.949
	30	1986.912	6009191	2451.365	0.936

	60	1264.653	3263154	1806.420	0.961
	200	812.944	1115860	1056.343	0.775
Bitcoin, Volume, VT, Euro, and Silver	7	1374.407	3907323	1976.695	0.960
	30	2257.876	7659103	2767.508	0.918
	60	1270.987	3503748	1871.830	0.958
	200	804.615	1075722	1037.170	0.783
Bitcoin, Volume, VT, Euro, and Copper	7	1758.194	5208619	2282.240	0.946
	30	4504.198	24669041	4966.794	0.737
	60	5505.644	37437067	6118.584	0.554
	200	4283.804	20144311	4488.242	-3.069
Bitcoin, Volume, VT, Silver, and Copper	7	1701.681	4941126	2222.864	0.949
	30	2149.957	6844963	2616.288	0.927
	60	1263.679	3302852	1817.375	0.961
	200	828.393	1140919	1068.138	0.770
Bitcoin, Volume, Israeli New Shekel, Euro, and Silver	7	1648.541	4462591	2112.485	0.954
	30	1630.669	5172864	2274.393	0.945
	60	1247.051	3515039	1874.844	0.958
	200	966.028	1514405	1230.612	0.694
Bitcoin, Volume, Israeli New Shekel, Euro, and Copper	7	1865.045	5777503	2403.644	0.941
	30	5293.756	33562754	5793.337	0.642
	60	4532.207	25787001	5078.090	0.693
	200	5843.218	37221043	6100.905	-6.519
Bitcoin, Volume, Israeli New Shekel, Silver, and Copper	7	1544.486	4489002	2118.727	0.954
	30	1405.062	3955932	1988.952	0.958
	60	1335.235	3545457	1882.938	0.958
	200	846.945	1319503	1148.696	0.733
Bitcoin, Volume, Euro, Silver, and Copper	7	2091.617	6612870	2571.550	0.932
	30	3227.873	13241103	3638.833	0.859
	60	1956.824	5845226	2417.690	0.930
	200	4158.820	18692155	4323.443	-2.776
Bitcoin, VT, Israeli New Shekel, Euro, and Silver	7	1631.403	4558391	2135.039	0.953
	30	2396.329	8838239	2972.917	0.906

	60	1256.983	3416486	1848.374	0.959
	200	922.903	1520094	1232.921	0.693
Bitcoin, VT, Israeli New Shekel, Euro, and Copper	7	2214.282	7329656	2707.334	0.925
	30	4524.218	25008629	5000.863	0.733
	60	3325.045	15070442	3882.067	0.820
	200	2162.969	6264339	2502.866	-0.265
Bitcoin, VT, Israeli New Shekel, Silver, and Copper	7	1489.019	4651401	2156.711	0.952
	30	1853.297	5340733	2311.003	0.943
	60	1418.385	4035551	2008.868	0.952
	200	1116.811	1969272	1403.308	0.602
Bitcoin, VT, Euro, Silver, and Copper	7	1955.634	5995828	2448.638	0.938
	30	5102.626	32582682	5708.124	0.653
	60	3153.879	13311176	3648.448	0.841
	200	5476.280	33715942	5806.543	-5.811
Bitcoin, Israeli New Shekel, Euro, Silver, and Copper	7	2041.496	6508072	2551.092	0.933
	30	4768.229	28507788	5339.269	0.696
	60	3151.403	13197359	3632.817	0.843
	200	2669.378	8875571	2979.190	-0.793
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Silver	7	1409.983	3770845	1941.866	0.961
	30	1951.748	6321102	2514.180	0.933
	60	1142.855	3071265	1752.503	0.963
	200	1212.906	2042070	1429.010	0.588
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Copper	7	1801.421	5499098	2345.016	0.944
	30	4773.689	26698563	5167.065	0.715
	60	2687.192	10130955	3182.916	0.879
	200	4539.884	22535119	4747.117	-3.552
Bitcoin, Volume, VT, Israeli New Shekel, Silver, and Copper	7	1895.002	5731494	2394.054	0.941
	30	2904.888	11084568	3329.350	0.882
	60	1314.726	3594763	1895.986	0.957
	200	1023.260	1587967	1260.146	0.679
Bitcoin, Volume, VT, Euro, Silver, and Copper	7	1677.529	4954925	2225.966	0.949
	30	4220.052	21529732	4640.014	0.770

	60	2428.929	8406846	2899.456	0.900
	200	6373.651	42835574	6544.889	-7.653
Bitcoin, Volume, Israeli New Shekel, Euro, Silver, and Copper	7	2862.163	10999597	3316.564	0.887
	30	4450.634	24317316	4931.259	0.741
	60	3119.376	12722323	3566.837	0.848
	200	2876.311	10224974	3197.651	-1.065
Bitcoin, VT, Israeli New Shekel, Euro, Silver, and Copper	7	2702.078	10046354	3169.598	0.897
	30	4068.310	20330615	4508.948	0.783
	60	1802.309	5785726	2405.354	0.931
	200	3613.730	15273196	3908.094	-2.085
Bitcoin, Volume, VT, Israeli New Shekel, Euro, Silver, and Copper	7	2406.417	8447664	2906.487	0.913
	30	5471.761	36817863	6067.773	0.607
	60	1883.799	5912430	2431.549	0.929
	200	4833.209	28377166	5327.022	-4.732

APPENDIX K

Combination	MAE	MSE	RMSE	MAPE	Coverage
Bitcoin and Volume	11565.284	270444519	15394.594	0.619	0.236
Bitcoin and VT	12499.608	280180188	15994.866	0.703	0.124
Bitcoin and Israeli New Shekel	14741.999	340932721	17727.613	0.948	0.071
Bitcoin and Euro	14738.190	353318963	17845.264	1.031	0.162
Bitcoin and Silver	15063.705	3688827156	18120.942	1.057	0.232
Bitcoin and Copper	14226.479	321839512	16961.423	1.020	0.186
Bitcoin, Volume and VT	10251.142	225374718	14179.030	0.489	0.268
Bitcoin, Volume, and Israeli New Shekel	11435.636	259327255	15192.232	0.570	0.182
Bitcoin, Volume and Euro	11591.913	264723396	15205.077	0.659	0.193
Bitcoin, Volume and Silver	12099.337	284143893	15638.198	0.722	0.282
Bitcoin, Volume and Copper	11336.180	265713111	15035.042	0.651	0.279

Bitcoin, VT, and Israeli New Shekel	13114.302	302919351	16690.709	0.723	0.078
Bitcoin, VT, and Euro	12295.493	273874783	15826.577	0.711	0.129
Bitcoin, VT, and Silver	12478.910	280590149	15870.721	0.741	0.211
Bitcoin, VT, and Copper	11585.744	229561180	14383.326	0.717	0.188
Bitcoin, Israeli New Shekel and Euro	14370.858	327351802	17335.462	0.962	0.072
Bitcoin, Israeli New Shekel and Silver	14939.523	345928146	17675.493	1.011	0.087
Bitcoin, Israeli New Shekel and Copper	13839.312	290246996	16217.473	0.980	0.077
Bitcoin, Euro, and Silver	15065.741	367370200	18049.307	1.074	0.198
Bitcoin, Euro, and Copper	14505.090	324350027	17010.200	1.059	0.099
Bitcoin, Silver, and Copper	14198.780	345683960	17505.184	0.961	0.193
Bitcoin, Volume, VT, and Israeli New Shekel	10737.950	245209651	14823.599	0.493	0.193
Bitcoin, Volume, VT, and Euro	9875.524	213280020	13769.638	0.479	0.290
Bitcoin, Volume, VT, and Silver	10826.911	239608772	14501.488	0.589	0.323
Bitcoin, Volume, VT, Copper	9584.662	206810243	13390.015	0.488	0.340
Bitcoin, Volume, Israeli New Shekel, and Euro	11574.322	255224185	15062.231	0.615	0.138
Bitcoin, Volume, Israeli New Shekel, and Silver	11796.058	263583035	15180.349	0.653	0.197
Bitcoin, Volume, Israeli New Shekel, and Copper	11045.341	244591225	14534.552	0.599	0.193
Bitcoin, Volume, Euro, and Silver	12316.301	285437418	15668.857	0.751	0.265
Bitcoin, Volume, Euro, and Copper	11506.071	270584332	15167.089	0.663	0.277
Bitcoin, Volume, Silver, and Copper	11319.708	287879516	15606.854	0.606	0.302
Bitcoin, VT, Israeli New Shekel and Euro	12900.606	290027820	16319.451	0.770	0.088
Bitcoin, VT, Israeli New Shekel and Silver	13127.773	297656686	16386.827	0.779	0.076
Bitcoin, VT, Israeli New Shekel and Copper	12085.724	239639406	14752.911	0.762	0.090

Bitcoin, VT, Euro, and Silver	12775.146	284439276	16000.673	0.765	0.130
Bitcoin, VT, Euro, and Copper	12001.617	242168299	14756.278	0.769	0.100
Bitcoin, VT, Silver, and Copper	11655.576	259130146	15167.373	0.664	0.216
Bitcoin, Israeli New Shekel, Euro, and Silver	15083.138	350354501	17777.843	1.024	0.066
Bitcoin, Israeli New Shekel, Euro, and Copper	13773.661	280792905	15986.595	0.986	0.074
Bitcoin, Israeli New Shekel, Silver, and Copper	13747.228	306721775	16627.330	0.911	0.064
Bitcoin, Euro, Silver, and Copper	14219.345	352525508	17633.295	0.952	0.189
Bitcoin, Volume, VT, Israeli New Shekel, and Euro	10307.260	228076864	14249.641	0.487	0.219
Bitcoin, Volume, VT, Israeli New Shekel, and Silver	11097.708	248256835	14789.045	0.584	0.247
Bitcoin, Volume, VT, Israeli New Shekel, and Copper	9956.579	216426309	13708.768	0.497	0.238
Bitcoin, Volume, VT, Euro, and Silver	10670.996	233807324	14324.717	0.574	0.292
Bitcoin, Volume, VT, Euro, and Copper	9721.373	207347465	13402.827	0.505	0.318
Bitcoin, Volume, VT, Silver, and Copper	9979.627	233366054	14172.986	0.489	0.358
Bitcoin, Volume, Israeli New Shekel, Euro, and Silver	12212.112	269744376	15370.218	0.695	0.144
Bitcoin, Volume, Israeli New Shekel, Euro, and Copper	11271.070	245170052	14570.863	0.627	0.161
Bitcoin, Volume, Israeli New Shekel, Silver, and Copper	11240.391	268087167	15183.085	0.574	0.197
Bitcoin, Volume, Euro, Silver, and Copper	11343.070	278223923	15359.974	0.621	0.296
Bitcoin, VT, Israeli New Shekel, Euro, and Silver	13152.462	296419409	16355.150	0.790	0.100
Bitcoin, VT, Israeli New Shekel, Euro, and Copper	12054.137	235784681	14648.499	0.770	0.094
Bitcoin, VT, Israeli New Shekel, Silver, and Copper	12594.114	288922420	16031.208	0.735	0.082
Bitcoin, VT, Euro, Silver, and Copper	12457.539	290508377	15977.134	0.735	0.113

Bitcoin, Israeli New Shekel, Euro, Silver, and Copper	13721.783	319685255	16916.756	0.883	0.084
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Silver	11052.683	242312424	14600.860	0.578	0.214
Bitcoin, Volume, VT, Israeli New Shekel, Euro, and Copper	9975.523	212762767	13603.688	0.509	0.233
Bitcoin, Volume, VT, Israeli New Shekel, Silver, and Copper	10424.617	251167480	14706.495	0.494	0.258
Bitcoin, Volume, VT, Euro, Silver, and Copper	10059.955	236903654	14242.153	0.491	0.330
Bitcoin, Volume, Israeli New Shekel, Euro, Silver, and Copper	11642.826	273765302	15343.883	0.621	0.173
Bitcoin, VT, Israeli New Shekel, Euro, Silver, and Copper	12207.681	283393704	15860.780	0.693	0.111
Bitcoin, Volume, VT, Israeli New Shekel, Euro, Silver, and Copper	10392.033	244657712	14514.640	0.500	0.239