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Forecasting prices of Bitcoin and Google stock with ARIMA vs Facebook Prophet

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Foreword

I want to thank University west, Maher Asal and Urban Gråsjö who inspired me to do this paper. I especially want to thank Hakan Inal who helped me to reach my goal in time.

BACHELOR'S THESIS

Forecasting prices of Bitcoin and Google stock with ARIMA vs Facebook Prophet

Abstract

In this thesis we have presented econometrics and forecasts of Bitcoin and Google (GOOG) prices. We have implemented two models, one traditional, "ARIMA" and a relatively new one, "Prophet model" by using Facebook Prophet (ML). Machine learning is still new in the economic field, it has been rewarding to learn its capability. We have evaluated the model's performance by using root mean square error (RMSE) and compared the result which model performed better. We wanted to compare to different assets, volatile Bitcoin to considerable stable Google (GOOG), thus investigate our models performance and if they differ or not. Regarding our result, we found that the ARIMA models have the best forecasting ability. We also investigate the impact of rational expectation and its impact on an asset price. We found that announcements on Bitcoin cause a significantly change in price and had an impact on the model's performance.

Abstrakt

I denna avhandling har vi presenterat ekonometriska modeller och prognoserade prisnivåer av Bitcoins och Googles (GOOG). Vi har implementerat två modeller, en traditionell, "ARIMA" samt en relativt ny modell, "Profetmodellen" med Facebook Prophet (ML). Maskininlärning är fortfarande nytt inom det ekonomiska området och det har varit givande att förstå dess förmåga. Vi vill jämföra två typer av tillgångar, Bitcoin som är volatile mot Google som är förhållandevis stabil för att se om våra modeller skiljer sig åt. Vi har utvärderat modellens prestanda med hjälp av root mean square error (RMSE) och jämförde resultatet vilken modell som var mest exakt. Vi fann att ARIMA-modellen gav oss bäst resultat. Vi undersöker också effekterna av rationella förväntningar och dess inverkan på pris av tillgång. Vi fann att nyheter om Bitcoin influerar dess pris och hade en inverkan på modellernas prestanda.

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Nomenclature

Vocabulary

Technical Analysis- Technical analysis is a means of examining and predicting price movements in the financial markets, by using historical price charts and market statistics

Autoregressive model- Autoregressive" (AR) model is based regressions on previously data. The term "auto" means "self", thus autoregression is a regression of a variable and lags of itself.

Machine Learning- Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention.

Supervised Learning- Supervised learning (SL) is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. It infers a function from labeled training data consisting of a set of training examples.

Keywords: Facebook Prophet, ARIMA, Google, Bitcoin

1. Introduction

It is merely a utopian dream to be able to see into the future. Nonetheless a driving factor for statisticians and theorists in their attempts to develop new models and methods to achieve as accurate forecasts as possible. One way to this is by studying a company and the market where the company is established by work on a fundamental analysis. The technical analysis is however the most important element in forecasting and is based on historical data over price of a stock. These price movements are fundamental drivers for the next day, month or year predicted price.

Models can be extended to get more predictable forecasts by adding more parameters such as dividend, technical improvement, or a crisis. The real challenge is to know when to stop or you might end up with more data than you can chew with a poor performance, inaccurate results and may also be time-consuming. Which lead to the main question in this paper. Which model has the better forecasting ability when predicting price of Google and Bitcoin? We choose Bitcoin and Google because how different they are to another, Google stock price (GOOG) is considered be stable while Bitcoin is well known to be volatile. We want to investigate how our models will react to this.

Bitcoin is known to have weak relationship with Macro variables, however a recent study by (Lyocsa et al., 2020) show that announcement have explanatory power over Bitcoin price. This is something that we will investigate when we evaluate a model's performance when predicting price of Bitcoin. It is well known that the stock market is built on expectation that are influenced by dividends, technology progress, innovations, and other announcements. When Elon musk invested 1.5 billion in Bitcoin in February 2021, he also announced that Tesla would accept Bitcoin as payment. Investors' expectations increased rapidly to the good news which led to the cryptocurrency skyrocket and reached all-time high of $63,503. How will announcement and rational expectation influence our forecasts?

The historical data for forecasting i.e., stock prices are available visually to everyone and is reasonable to consider it as a valuable factor in the technical analysis. Stock-price may also rely on other parameters such as vacations, holidays or even weather. These parameters can be used to test hypothesis or find a trend, notified as cyclical pattern in the time-series data. In this paper we will use passed prices of Bitcoin and Google to forecast future price movements. We are going to apply two different models. The first model that we are going

to use is the Autoregressive integrated moving average model (ARIMA) and the second is the Prophet model by Facebook Prophet (ML). Facebook Prophet is an AI, that are based on supervised learning algorithm. Machine learning (ML) can be explained as a method of data analysis that automates analytical model building. It is an artificial intelligence based on the idea that systems can learn from data. It is recognizing patterns and make decisions with minimal human intervention. We will finally evaluate and compare which one models create most accurate forecasts when predicting prices.

1.1 Purpose

The goal with this thesis is to evaluate the Prophet model´s and ARIMA model´s forecasting ability when forecasting price of Bitcoin and Google stock, using historical data from 1st January 2015 – 4th May 2021. Secondly, we will use rational expectation theory to investigate if announcement affect our models forecasting ability.

2. Literature review

In this report, the focus is on forecasting share price for Google and exchange rate for the cryptocurrency, Bitcoin. The models that will be applied are based on empirical data. To this day theorists and statisticians still struggles to find the perfect model to predicting prices for stocks nonetheless for Bitcoins. Unfortunately, there are no perfect formula to predict price movements. (Hill et al., 2010) explain that the autoregressive models are mainly used for forecasts. (Koop, 2013) confirm this and write that the Autoregressive model is proven from previously studies to have great forecast ability.

2.1 Previous work

We will present previous research papers that have used Autoregressive model integrated model (ARIMA) to make forecasts. (Amos et al., 2013), study was designed to look at the behaviour of stock price of Nigerian Breweries Plc with passage of time and to fit Autoregressive Integrated Moving Average, by using filter for the prediction of stock price of the Nigerian Breweries Plc. The ARIMA model is many times preferred because it´s good at detecting outliers in the dataset and is proven to be accurate, thus a good candidate to the Prophet model.

(Arslan et al.,2018) used Facebook prophet to make their forecasts of Bitcoin price. The models selection for both ARIMA, and PROPHET was done by using threefold splitting technique considering the time series characteristics of the dataset. The threefold splitting technique gave the optimum ratios for training, validation, and test sets. Facebook prophet can be used even without training data according to Facebook science team. This suggest that we going to use parameters in the Prophet model set as default and without tuning any hyperparameters.

(Arslan et al.,2018), evaluate the models they used with Root mean square error. RMSE often used when evaluating different models since it can handle different units. MAPE for instance evaluate forecasts in percentage which cannot be used when forecasting temperature for instance. This suggests we are going primarily use Root mean square error when evaluating our model's performance.

(Jackson et al., 2020), in their study they used Auto-Regressive Integrated Moving Average (ARIMA) model to make predictions of stock prices on Indian stock market. They tested stationarity of the timeseries data by using Augmented Dickey-Fuller test and Monte Carlo Model to tell possible future predictions of stock for some time. They used Prophet library by Facebook, thus it is very robust in processing the time series data and giving future predictions based on a daily trend of data, a weekly trend of data and yearly trend of data.

(Devi et al., 2013) used NIFTY MIDCAP 50 as the index and selected the top four MIDCAP companies. They used ARMA and ARIMA models to predict future stock prices and used Akaike information criterion and Bayesian information criterion (AIC and BIC) to get the best fit for the model.

The authors (Mondal et al., 2014) did a study on the effectiveness of the ARIMA model in forecasting security values. They used Indian Stock market data from NSE for the analysis and AIC has been used for selecting the best ARIMA model. AIC and BIC are often used when selecting model to get the best results.

One way to set stock prices is through Momentum and can be explained by following. An investor is mainly looking at two types of prices, current price and selling price. Previous prices from historical price indices affects the investor's behaviour and depends on the buying situation and the market situation. “Don't fight the tape" Is a famous piece of words of wisdom to an investor, not to be fooled by market trends. Momentum suggests that the best way to predict the market is by looking at the movement of the market, in which direction it is going. Momentum is based on consumer behavior, why hold on to a stock that falls instead of one that climbs and is a classic example of fear and greed. A study by (Jegadeesh & Titman, 1993) conclude that individual stocks have Momentum. They found that stocks that have performed well in recent months are more likely to continue to perform next month. This also includes stocks that have performed poorly are more likely to continue their poor performance. However, this study looked only forward 3 to 12 months. For longer periods, however, the momentum effect seems to be reversing. According to (Bondt & Thaler, 1985), it turned out that stocks that have performed well over the last three to five years are more likely to underperform the market over the next three to five years and vice versa. The momentum strategy suggests that we going to make a short-term prediction within the timeframe of 12 months.

3. Theoretical framework

3.1 Rational Expectations Theory

The rational expectations theory posits that individual base their decisions on three primary factors: their human rationality, the information available to them, and their past experiences. The rational expectations theory is often used in macroeconomics when explaining economic factors such as inflation rates and interest rates how they are connected to people's rationality and decision-making. The foundation of this theory is that past outcomes influence future outcomes. And those peoples make decisions based on the available information combined with their past experiences and that these decisions are rational and most of the time correct.

Current Expectation continuously evolving from previously outcomes and experiences. Some events may happen more than one time this suggest according to the theory create a pattern, thus influence people to adjust their forecasts to fit this pattern. A quote by Abraham Lincoln describes this well, "You can fool some of the people all of the time, and all of the people some of the time, but you cannot fool all of the people all of the time". From the perspective of rational expectations theory, People will make forecasting errors, but certain errors will be considering when forecasting again. Naturally, people learn from mistakes, both previously experience combine with the available information when they make decisions. Thereby will most of the time be correct. If they get it right, the expectations for the future will happen. If they get it wrong; they will adjust their decision-making accordingly. The theory suggests that people's current expectation of i.e., a stock, are themselves able to influence what the future will hold. If enough people believe a stock will increase in price based on available information what they experienced in the past, their expectations will occur. Investors who think that the price of a share of stock will go up, will try to buy shares before others do. However, if everyone tries to buy shares at the same time, share prices will go up because of the overall increase in demand. We will analyze the history of price movements of Google and Bitcoin separately to see if any announcement had a significant impact on the assets price that specific period.

4. Methodology

The goal with this thesis is to evaluate Prophet model and ARIMA model forecasting ability when forecasting price of Bitcoin and Google. We are also going to investigate if announcement and rational expectation affect our forecasting result. The process of our work:

1. Collect daily historically data between period 1st January 2015- 3rd May 2021 for Google (GOOG) and Bitcoin.
2. Use ARIMA in SPSS and Facebook Prophet (ML) in Python3 to forecasting prices of Google stocks and Bitcoin during a 14- Day forecast between 4th May 2021 – 17th May 2021.
3. Evaluate and compare the models using RMSE to determine which model producing the better forecasts.
4. Investigate if announcements and "Rational expectations" have an impact on an asset in our forecasts.

4.1 Technical analysis

The purpose of a technical analysis is to examine and predicting price movements in the financial markets, by using historical price charts and market statistics. It is based on the idea that if a trader can identify previous market patterns, they can form a fairly accurate prediction of future price trajectories. Technical analysis is often used to generate short-term trading signals from various charting tools but can also help improve the evaluation of a security's strength or weakness relative to the broader market or one of its sectors. This information helps analysts improve their overall valuation estimate.

4.2 Autoregression model

Autoregressive" (AR) model is based regressions on previously data. The term "auto" means "self", thus autoregression is a regression of a variable and lags of itself. The first formula is an autoregressive model with the explanatory variable being the dependent variable lagged one period. AR (p) model:

$$Y_t = \alpha + \delta_t + \rho Y_{t-1} + \cdots + Y_{t-p} + \varepsilon_t$$

Equation 1 AR(p) model

In the equation above, "Y_t" the depends on its lags from the last periods, denoted "p" and random error (e_t) that is assumed to have a zero mean and a constant variance, and to be uncorrelated over time. Since we only use dependent variable and lag of the dependent variable, thus the value of Y depends only on a history of its past values and no x's.

4.3 Sequential method

We will take the natural logarithm of the timeseries data and create lags of the dependent variable "Y_t" and run first order autoregression, where we sequentially test lags significance. We will use OLS to test significance of our lags by focusing on recording high t-statistics and low p-values (<0.05), then omit lag lengths that are insignificant (>0.05).

4.4 Unit-root hypothesis

We will perform a Dickey-Fuller and test unit-root on "Y_{t-1}" null hypothesis (p=0). If p=0 then this suggest that we should take the natural logarithm of our variable then differentiate and lagged it one time, then run the regression again. then this suggest that we should

differentiate our data then lag it one time, then run the unit-root test again. We will proceed to do this till our time-series is stationary (2<p<0).

4.5 Autoregression integrated moving average

An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends. Each component of the ARIMA model can be explain where "AR", refers to a model that regresses on its own lags. Integrated "I" stands for differencing of raw observations allow the time series to become stationary. Moving Average "MA" incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations. The data are differenced to make it stationary where the data show is constancy over time. The purpose of differencing is to remove any trends or seasonal structures.

4.6 Implementing ARIMA

Auto-regressive integrated moving average (ARIMA) model is an extension of the ARMA, model is denoted as ARMA (p, q). Where, p denotes the number of autoregressive terms and d denotes number of differences. In the ARIMA(p,d,q) model, "Y_t" is dependent also on and "d", the number of non-seasonal differences is needed to make the time-series stationary. "e_t" is the Gaussian distributed white noise "q", denotes the number of errors which the models should include. "p" is number of lags of the dependent variable included in the model.

$$Y_t = \alpha + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \emptyset_1 \varepsilon_{t-1} \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Equation 2 ARIMA(p,d) model

The equation below is an "ARIMA(1,1,0) model. which is Y_t regressed on itself lagged by one period If the mean of Y is zero, then the constant term would not be included. The ARIMA (1,1,0) can be written as:

$$\Delta Y_t = \alpha + \emptyset_1 Y_{t-1} + \varepsilon_t$$

Equation 3 ARIMA (1,1,0)

If the slope coefficient ϕ_1 is positive and less than 1 in magnitude (it *must* be less than 1 in magnitude if Y is stationary), the model describes mean-reverting behavior in which next period's value should be predicted to be ϕ_1 times as far away from the mean as this period's value. If ϕ_1 is negative, it predicts mean-reverting behavior with alternation of signs, i.e., it also predicts that Y will be below the mean next period if it is above the mean this period.

4.7 Supervised learning

Supervised learning (SL) maps a set of inputs, often referred to as features i,e "x" or vectors to a set of outputs often referred to as target variable, "y". These input-output pairs the target variable corresponds to a non-negative real value, in regression task of the Machine learning. A supervised learning algorithm analyzes the data and produces a function based on it. The goal is to allow the algorithm to determine class labels for unseen instances by construct model that utilize previously unseen inputs x to predict an estimation of the target variable y with minimal error.

4.8 Prophet model

Prophet based on supervised learning algorithm and is an open-source software that is available in Python and R for forecasting time series data. Prophet is published by Facebooks core Data science team. It depends on a contribution model where non-linear trends can be fit with yearly and weekly seasonality and holidays. We do not need to process our data to make forecasts, the prophet model can work with non-stationary time-series, and it is strong to handle missing data. It captures the shifts in the trend and is good at handle large outliers. In addition to this is also very effective it does not require too much effort to make good prediction. Prophet is optimized for business forecast that are observed on Facebook. For example, time, daily, weekly observations of history within a year, large outliers, trends,

missing observation, and trend that non-linear. Prophet framework has its own special data frame handle time series and seasonality easily. The data frame needs to be converted to basic columns. The first columns "ds", stores the time series data and the other column is "y", and it stores the corresponding values of the time series in the data frame. Prophet model can be set to handle seasonality of the dataset. These options are daily, weekly, and yearly seasonality and provide granularity for the forecast model on the dataset.

4.9 Implementing Prophet model

The mathematical equation behind the Prophet model is defined as:

$$y(t) = g(t) + s(t) + h(t) + e(t)$$

Equation 4 The prophet model

- g(t) representing the trend.
- s(t) represents periodic changes (weekly, monthly, yearly).
- h(t) represents the effects of holidays (Holidays that impact businesses).
- e(t) is the error term.

We will run Facebook prophet in Python3 by implementing additive regression model. It can be written as:

$$Y(t) = G(t) + S(t)$$

Equation 5 Additive regression

Linear trend

Breaking down the Prophet model, we start with the core component, the linear trend "G(t)". "G(t)" represents growth rate variable "k" as well as change in growth rate at the time "t". To this we can add offset parameter "m" and adjust the offset parameters to connect the endpoints of segments "γ", such as set of change points.

$$G(t) = k + a(t)^t\delta + (m + a(t)^t\gamma)$$

Equation 6 Linear trend

Seasonality

The second component in the Prophet model is the seasonality "s(t)" and is based on Fourier series which is a combination of weighted Cosines and Sinuses. In the formula below, "p" represents periods and "n" represent the order of Fourier series.

$$s(t) = a_0 + \sum_{n=1}^{\infty} \left(a_n \cos\frac{n\pi x}{P} + b_n \sin\frac{n\pi x}{P}\right)$$

Equation 7 Fourier series

X(t) is vector of Cosines and Sinuses, and beta is vector of all weights. We use seasonality model parameter set on yearly seasonality where n=10 and p= 365,25. The formula for Yearly seasonality is:

$$\mathrm{X(t)} = [\cos(\frac{2\pi(1)\mathrm{t}}{365.25}) \ldots \sin(\frac{2\pi(10)\mathrm{t}}{365.25})]$$

Equation 8 Fourier series and yearly seasonality

The seasonal component is present in equation below where "β" is normally distributed, $N(0, \sigma^2)$, where sigma regulates the strength of seasonality. It is used to smoothing prior in the seasonality.

$$\mathrm{S(t)} = \mathrm{X(t)}\beta$$

Equation 9 Seasonality Component

4.10 Evaluation of Models performance

The last step is to evaluate and compare our models and the results and estimate which model has the better forecasting ability. We will be comparing the results by implementing Root mean square error (RMSE). RMSE, yield the estimated value of the error square between the estimator and the true value of the parameter. (Everitt et al.,2010). When the RMSE is low, it means that the model is more accurate in forecasting. The result is obtained by first squaring the rate of the predicted observations subtracted with the actual observations. Then finding the average of the residuals by divide them with the sample size and finally take the square root of the mean.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y} - y)^2}{n}}$$

Equation 10 RMSE

5. The empirical work

5.1 Data Description

5.1.1 Bitcoin Data

In order to evaluate the model's performance, we need to gather, select features we want to interpretate in our models. The raw Bitcoin data was collected from Yahoo finance. We were only able to obtain historical data from 2015. This suggest that we will work with daily data, thus get reliable results. The data contain history of price movement from 1st January 2015 – 3rd May 2021. We will process our data to make sure its stationary when we run the ARIMA model. We will record announcement that have had significant impact on the assets price.

5.1.2 Google Data

The Google stock data (GOOG) was collected from Yahoo Finance. The raw data was collected from Yahoo finance, (1st January 2015 - 3rd May 2021). We will process our data for to make sure its stationary to make forecasts. We want to work two different types of assets and study its history price movements to find if announcement have had impact on price of Google (GOOG). We selected two different types of assets to analyze previous change in price. This can be useful when we interpretate our model's performance.

5.2 Descriptive statistics

5.2.1 Bitcoin price history

In this section we going to illustrate the data go through the descriptive statistics for the sample size that contains 2312 observations, 1st January 2015 – 3rd May 2021. The data contains open price, high price, low price, closing price and adjusted closing price and volume, were we going to work with Closing price (Close). The descriptive statistic of our data gives an overview of closing price, where we going to present this further in the next section. Table 1 show that Bitcoin minimum Closing price is $178,10 and reach at the highest price of $63,503.45. The mean is $7474. The standard deviation tells us about the spread, in

our case the data deviates by $11094 from the mean, the difference can be explained by Bitcoins high volatility.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Close	2312	178,102997	63503,457031	7474,56381546	11094,124723287

Table 1 Descriptive statistics Bitcoin

Bitcoin was released 2009 by pseudonymous Satoshi Nakamoto and offers the promise of lower transaction fees than traditional online payment mechanisms and, unlike USD for example, it is operated by a decentralized authority with no bank involved which makes it possible to make trade anonymously. Although this is tempting idea it also comes along with risks. Bitcoin investors have had a bumpy ride the last ten years, five of these years are illustrated in Figure 1, due to several problems such as multiple scams, fraudsters. Even so there are periods where bitcoin volatility swings have outpaced it normal daily swings, resulting in price bubbles. The first instance occurred in 2011 when Bitcoin's price jumped from $1 in April of that year to a peak of $32 in June with a growth of 3200% within three months. That steep ascent was followed by a sharp recession in crypto markets and Bitcoin's price fell and stopped at $2 in November 2011. The following year Bitcoin made a small improvement and the price had risen from $4.80 in May to 13.20$ by August. Things start to take off for Bitcoin and 2013 will be memorial when Bitcoin began to trade at 13.40$ and rise to 220$ in beginning of April and followed by deceleration by $70. Investors held their breath as Bitcoin spiked to $1156.10 and only few days later declining and fell by 760$ in December same year. Bitcoin slide through two years less dramatic till 2017. After a period of brief decline in the first two months, the price charted a remarkable ascent from $975.70 on March 25 to $20,089 on December 17. The 2017 hot streak also helped place Bitcoin firmly in the mainstream spotlight as new crypto currency as governments start to develop their own crypto currencies to complete with Bitcoin. However, in early 2018 both India and China announced regulation and implicated banks no longer could deal with transactions of cryptocurrencies. The People's Bank of China also announced the State Administration of

Foreign Exchange led by Pan Gongsheng would crack down on bitcoin mining. Many Bitcoin miners were affected and had stopped operating by January 2018. This influenced the price of Bitcoin negatively as it declined by $17527, 5th January 2018 to $9,119.01, 1st May 2018. In 2020 the year of the pandemic also synonym with declining stock prices and lockdowns, Bitcoin's price reached just under $24,000 in December 2020, an increase of 224% from the start of 2020. In less of a month Bitcoin beat its previous price record and surpass $40,000 in January 2021. This was caused by experts such as Steve Forbes, speculation about Bitcoin as an alternative to hedge against inflation from increased government spending during the pandemic. At its new peak, the cryptocurrency was changing hands at $41,528 on Jan 8, 2021. Three days later, however, it was at $30,525.39. On 8th February, Elon musk invested 1,5$ billion in Bitcoin and announced Bitcoin as payment method. This led to cryptocurrency peaked again and reached is all time off $63,503.45.

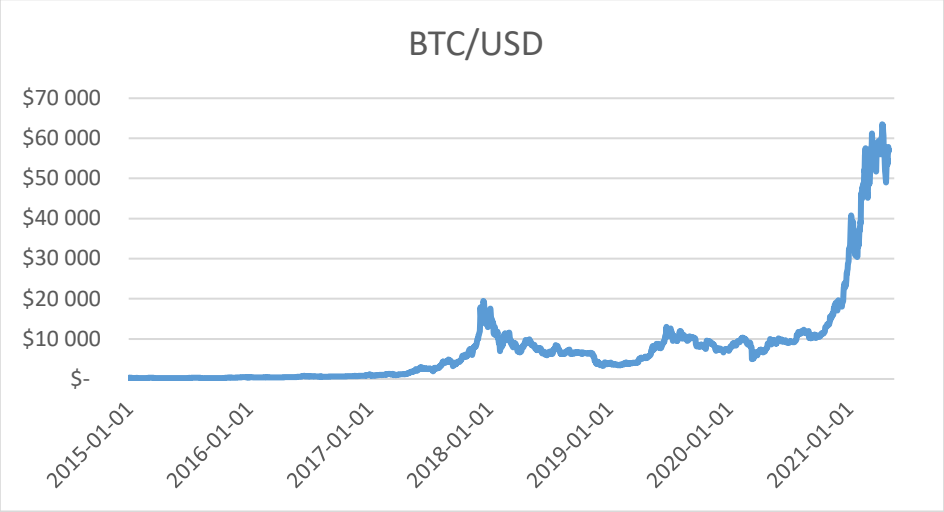

Figure 1 Bitcoin price history

5.2.2 Google price history

The descriptive statistic of Google contains 1595 observation (1st January 2015 – 3rd May 2021). (GOOG) minimum Closing price (Close) was $491,20 and reached maximum price $2429,88, 1st January 2015 – 3rd May 2021. The mean is $1063,76. The standard deviation tells us that the average distance of each observation lies $382,84 from the mean (Table 2).

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Close	1595	491,201416	2429,889893	1063,762330 44	382,8486491 32

Table 2 Descriptive statistics of Google

Google received its 1st round of venture capital funding in August 1998. Google registered the domain www.google.com on September 15, 1997. The company incorporated a year later September 7, 1998. Google went public on August 14, 2004. At the IPO, Google's founders offered 19,605,052 shares at a price of $85 per share and had made more than 23$ Billion in market capitalization. Google used the money well and did a major acquisition in October 2006, when company announced that it acquired streaming platform YouTube for 1.65$ billion dollars. In 2015 the company made a reconstruction and established parent company Alphabet Inc. (GOOG) in Mountain view, California. Alphabet became Googles multinational conglomerate headquarters. The two co-founders of Google remained as controlling shareholders, board members, and employees at Alphabet. Alphabet is the world's fourth-largest technology company by revenue and one of the world's most valuable companies. Alphabet released Q4 2019 earnings with $46.075 billion in revenue, according to its website, which stated, "These numbers range from October to December, and includes the busy holiday shopping season for Made by Google's hardware efforts." Google advertising service Google Ads and Search Advertising generated 162 billion dollars in 2019. Compared to Bitcoin, Google earn money on other companies' behalf. When new product or innovation are announced by company, a costumer who are interested will click on links

and pictures related to that announcement, thus Google get a stable source of income in this process. In 2020 The company became the first Technology company in US that is worth 1 trillion dollars. Majority of the company's revenue comes from advertising service from YouTube and Google Ads and can explains the Google stock (GOOG) nonaffected, up-going trend since WHO declared the COVID-19 pandemic in December 2019 (see Figure 2). In May 2021, stocks were traded by $2000 per share.

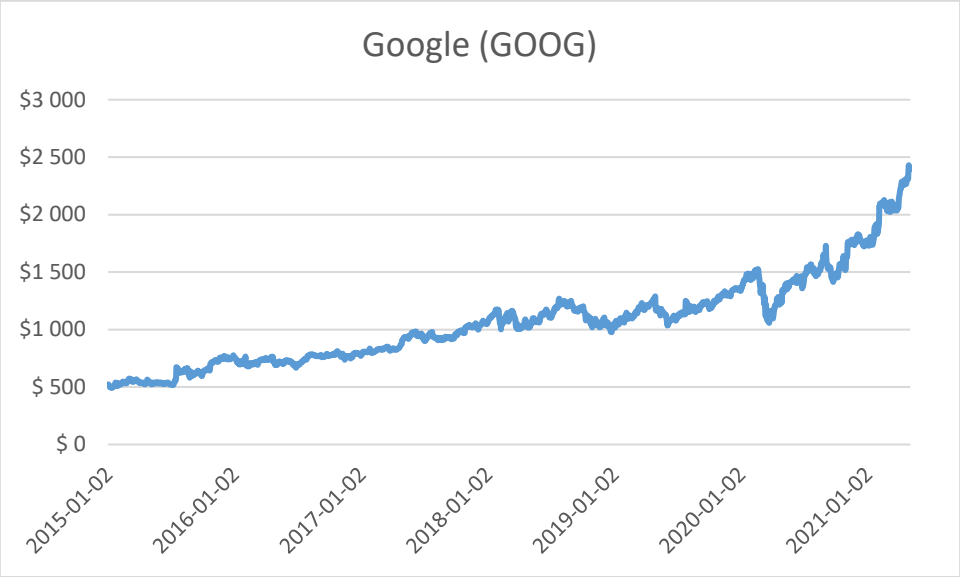

Figure 2 Google price history

5.4 Dickey-Fuller Test

We start to take the natural logarithm of the time-series data and create lags of the dependent variable, then run first order AR(p) and sequentially test lags significance. In our final model of the first order autoregression, p=0 and indicate that we got a unit root. This suggest that we should differentiate our time-series data and run the regression again. We did this procedure of both our timeseries of Bitcoin and Google. In our second order autoregression we choose max lag lengths of 5 lags of the depending variable Closing price "ΔY_t" and added deterministic trend variable. We omitted all the lags that was insignificant (>0,05). The first interpretation of Google (GOOG) closing price, show that the t-stat for "Y_{t-1}" is (-5,24), which is more negative than Dickey-Fuller critical value without deterministic trend (-2,863). We can reject unit-root null hypothesis (See table 3).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	,003	,008		,359	,720
	LAGS(Log,1)	,000	,001	-,006	-5,246	,006

a. Dependent Variable: DIFF(Log,1)

Table 3 Dickey-Fuller test of Google

The second interpretation of Bitcoin closing price show that the t-statistical is (-5,021), which is more negative than the Dickey-Fuller critical value without deterministic trend, (-2,863). We can reject unit-root null hypothesis; thus, our time-series are stationary (See table 4).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	,002	,004		,498	,619
	LAGS(log,1)	1,128E-5	,001	,000	-5,021	,005

a. Dependent Variable: DIFF(log,1)

Table 4 Dickey-Fuller test of Bitcoin

5.5 Model selection and interpretation

Our interpretation of the Dickey-fuller test tells us to differentiate our time-series data to get stationarity, thus suggest that we going to test AIC and BIC of our time-series data differentiated one time (d=1). The Akaike information criterion (AIC) is an estimator of prediction error and thereby relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection, where lower values of AIC is preferred to higher once. The Bayesian information criterion (BIC) is used for model selection among a finite set of models; the model with the lowest BIC is preferred.

Based on the estimation of AIC and BIC with Bitcoin closing price as dependent variable suggests that we will choose ARIMA (1,1,0). See Table 5 and Appendix 1.5.

	ARIMA (0,1,0)	ARIMA (1,1,0)	ARIMA (1,1,1)
AIC	-7970,524	-7972,497	-7971,491
BIC	-7953,452	-7961,115	-7960,800

Table 5 AIC and BIC of Bitcoin

Since we need to differentiate our time-series data over google, this suggest that we going to set d=1. The estimation of the quality of our models shows that the ARIMA (1,1,0) is best fit for forecasting price of Google (GOOG), see Table 6 and Appendix 1.6.

	ARIMA (0,1,0)	ARIMA (1,1,0)	ARIMA (1,1,1)
AIC	-8461,874	-8470,503	-8468,567
BIC	-8456,501	-8459,756	-8452,447

Table 6 AIC and BIC of Google

We run the regression of both variables of Bitcoin and Google separately and record the coefficients. The interpretation of ARIMA (1,1,0) model of each variable is:

Variable	Constant	Lag 1	Error term
Bitcoin	0,02	-0,011	0
Google	0,963	-0,065	0

Table 7 Interpretation of ARIMA (1,1,0)

6. Results

6.1 Forecasting price of Bitcoin

In our first forecast we use the Prophet model in Python. We use time-series data for both Bitcoin and Google from 1st January 2015 to 3rd May 2021 to make a 14-day forecast (4th May – 17th May) Then we calculate RMSE to evaluate our model's performance. The Prophet model use additive regression with a piecewise linear trend with yearly seasonality. Our flexibility of our model is set to default, thus prior changepoint prior scale is set to 0.05. Figure 3 illustrates Prophet model's performance. In the last section in this chapter, we have presented both models' performance. (See Figure 7 ARIMA (1,1,0) vs Prophet, 14-day forecast)

Features (Ds, y)	**Closing price, date**
Growth	Linear
Seasonality	Yearly
Prior changepoint prior scale	0.05
Variable	Bitcoin

Features (Y_t, Y_{t-1})	**Closing price**
P,d,q	1,1,0
Trend	Additive, Innovational, Level shift
Variable	Bitcoin

The ARIMA order is set to (1,1,0), where we use "Closing price" as dependent variable, "Y_t" and one lag of the dependent variable, "Y_{t-1}". We adjust our model to auto detect outliers, "Additive, Innovational and Level shifts". The ARIMA (1,1,0) model's performance is illustrated in Figure 5.

The last step is to evaluate and compare our model's performance using Root mean square error (RMSE). Lower values are preferred to higher once. According to our estimation of both our models (see Table 5), we found that ARIMA (1,1,0) performed better than the Prophet model by 0.05 RMSE to 230.68, Prophet model.

Model	RMSE	PRMSE	MAPE
Prophet	230.68	10.24%	6.36%
ARIMA(1,1,0)	0.05	0.00234%	0.002%

Table 8 RMSE table of Bitcoin A

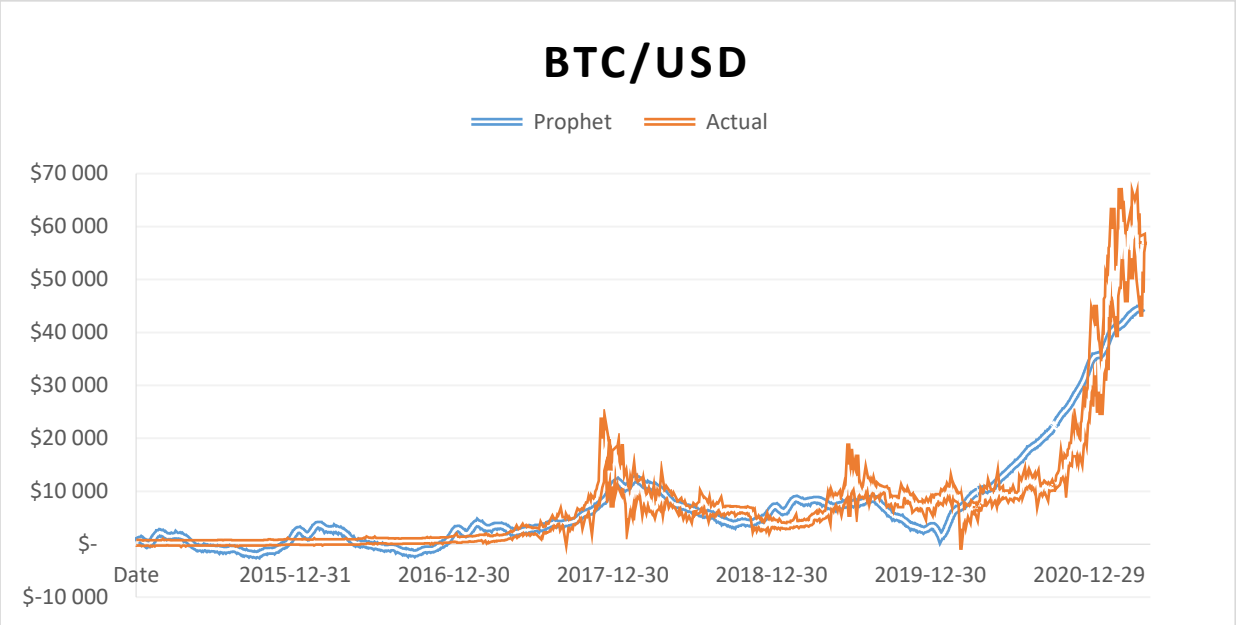

Figure 3 Prophet and Bitcoin

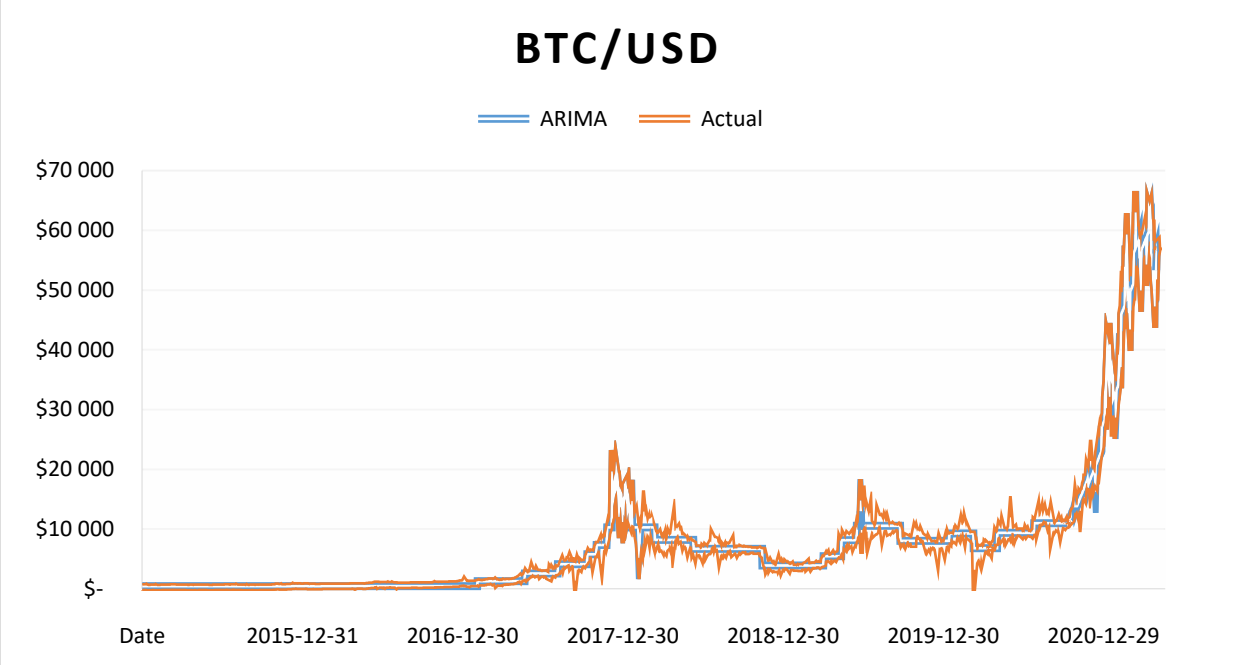

Figure 4 ARIMA (1,1,0)

6.2 Forecasting prices of Google stock

Features (Ds, y)	**Closing price, date**
Growth	Linear
Seasonality	Yearly
Prior changepoint prior scale	0.05
Variable	Bitcoin

The next forecast is of Google future price movements (4th May –17th May 2021). Our interpretation of the Prophet model gave us better result this time. All hyperparameters in the Prophet model was set on default, as we did in the previous forecast of Bitcoin. In the last section in this chapter, we have presented both model's performance to actual values of Google price. (See Figure 10 ARIMA (1,1,0) vs Prophet, 14-day forecast)

Features (Y_t, Y_{t-1})	**Closing price**
P,d,q	1,1,0
Trend	Additive, Innovational, Level shift
Variable	Bitcoin

We can clearly observe that both models were performing better when forecasting Google prices (GOOG) compared to Bitcoin. This is explained by the erratic behavior of Bitcoin previously prices movements. The evaluation of our model's performance is in Table 6. The ARIMA (1,1,0) model did almost a perfect prediction, thus performed slightly better than the Prophet model.

MODEL	RMSE	PRMSE	MAPE
Prophet	0.107	0.01%	0.0003%
ARIMA(1,1,0)	0.000003	0%	0%

Table 9 RMSE table of Google

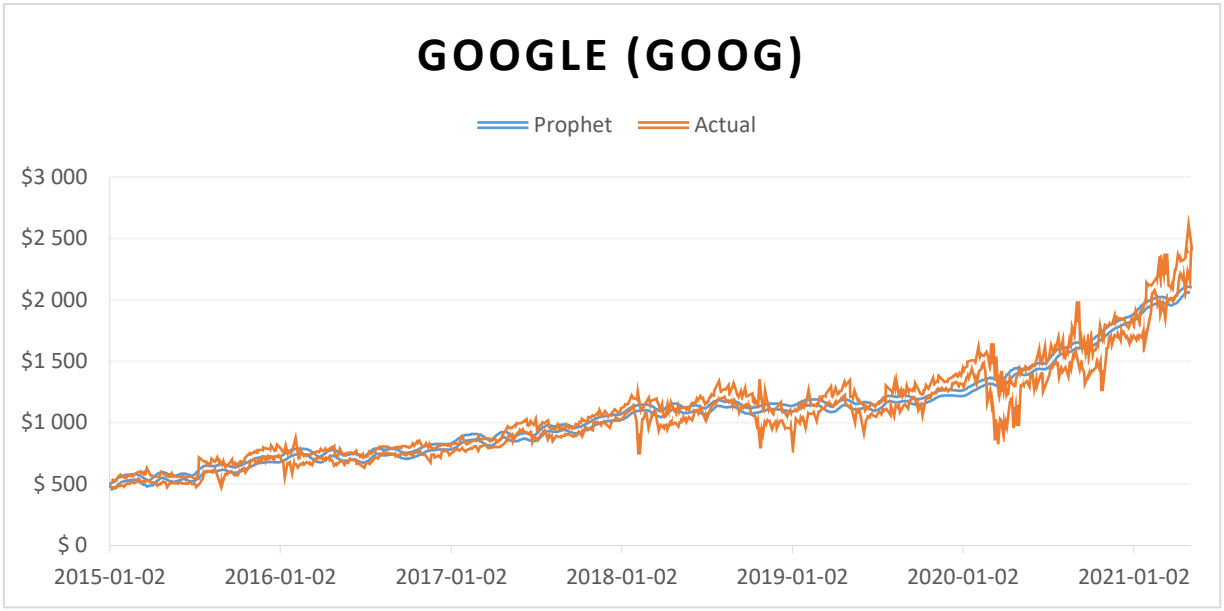

Figure 5 Prophet and Google

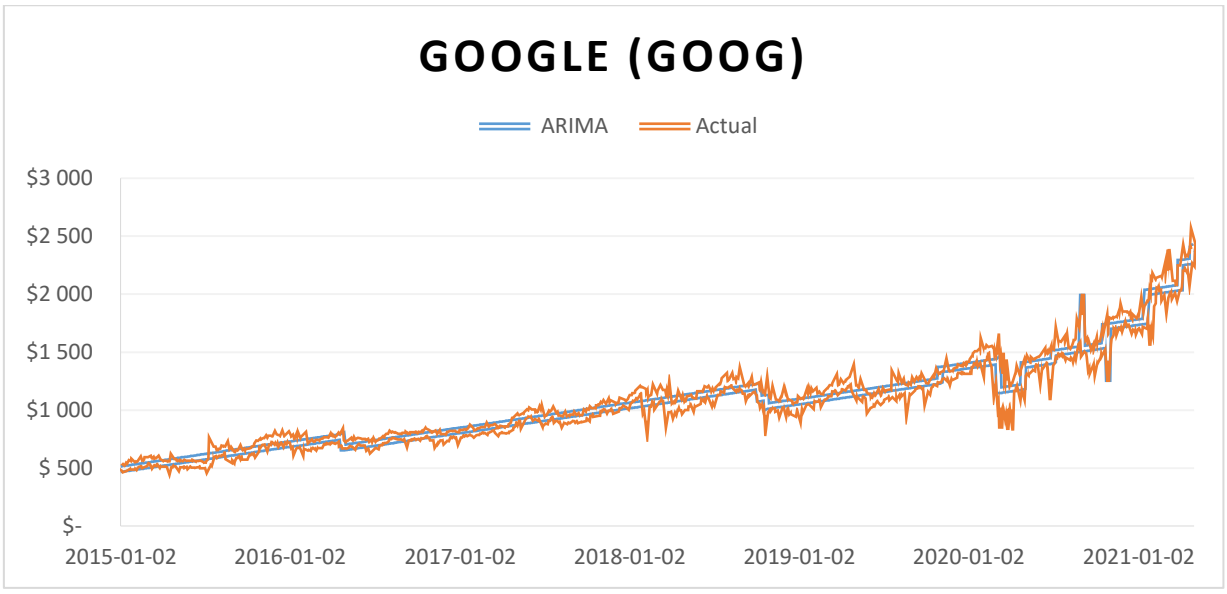

Figure 6 ARIMA (1,1,0) and Google

6.3 Forecast and expectation

The determents that influence the Bitcoin price is still a mystery, the cryptocurrency does not seem to have a stable relationship with macro variables such as inflation. However, a recent study shows that news has explanatory power over Bitcoin price. "The volatility of bitcoin is strongly influenced by news about bitcoin regulation. In particular, the volatility of bitcoin is significantly increased a day before an article about Bitcoin regulation is published in a newspaper, the Financial Times." (Lyocsa et al., 2020). This result is consistent with (Auer & Claassen, 2018), who suggest that regulation is a significant price factor for cryptocurrencies. Another research by (Zhu et al, 2020) show that the investors' attention granger causes both Bitcoin return and realized Volatility. "Besides, the impulse response from VAR models showed that shock from investors' attention may last for several weeks in Bitcoin market."

The market is driven by expectations and is something neo-Keynesian economics have agreed on since 1930. Announcement affect our expectations about a stock i.e., investors who have suffer heavy losses from previous decisions are more likely to be affected by good and bad news alike. The rational expectations theory suggest that expectations and outcome are linked, and that people's expectations and decision are influenced by all available information and experiences from previous mistakes and success. Similar to the rational expectation theory the Adaptive expectations theory suggest that people who expect price to rise will continue to do so the next period.

The rational expectation theory also suggest that we are not only depending on own experiences, but we also strive to learn from others by searching new sources of information when we decide about i.e., either hold or sell a stock. On 8th February 2021, Elon musk invested 1.5 billion dollars in Bitcoin, he also announced that you could buy a Tesla car in exchanged for Bitcoin. The announcement became hit, thus pushed expectation and Bitcoin prices upwards. This led to that the crypto currency peaked and weeks later reached a new price record of $65,343. Several days later, the price eventually decreased in response to the topicality of the announcement (See figure 9). Months later, 12th May 2021, he took the deal back because of Environmental concern of the high electric consumption from Bitcoin mining. This led to that people's expectation decreased and caused the price to drop notably.

After Elon Musk's announcement of taking back his promise of Bitcoin as payment for Tesla cars, the price of Bitcoin decreased by 16%, between 12th -17th May 2021. In Figure 7, we have presented our 14-day forecast of price of Bitcoin between 4th May – 17th 2021.

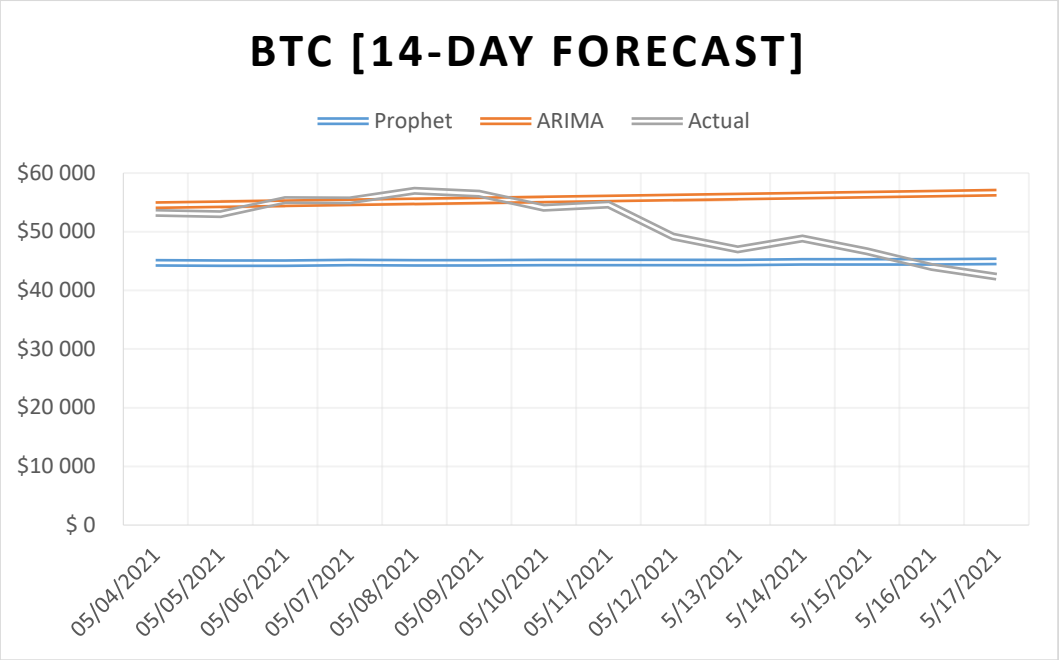

Figure 7 ARIMA (1,1,0) vs Prophet, 14-day forecast

ARIMA (1,1,0) have accurately predicted price of Bitcoin the first seven days but then deviate to the actual values when the price of Bitcoin plummet, 12th May 2021. The Prophet models in other hand, have accurately determined the last days of the forecast as it is intercepting the actual values, 16th of May. The last days of the forecast (12th – 17th May 2021), Prophet model was undeniably more accurate then ARIMA (1,1,0). Although ARIMA (1,1,0) was overall slightly more accurate.

Both ARIMA and Prophet model detects cyclical patterns in terms of trends. Announcement of Bitcoin cause the price to arise. Days after the announcement the price is decreasing accordingly to the announcement's topicality. This creates a pattern as illustrated in Figure 8, Where actual values of Bitcoin price to its mean is presented.

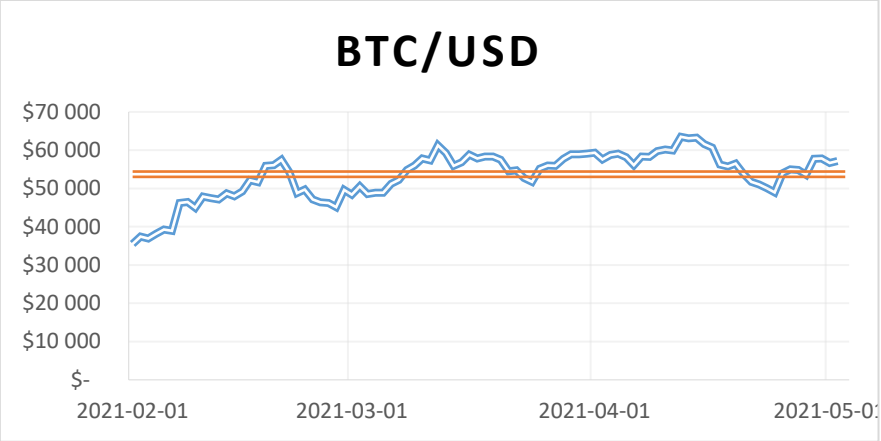

Figure 8 Cyclical patterns of Bitcoins price

We are going to present another forecast during a recent rally of Bitcoin. That was caused by that expert's speculation and future expectations about Bitcoin as an alternative to hedge against inflation from increased government spending during the pandemic. The use of Bitcoin for treasury management at companies also strengthened its price. MicroStrategy Inc. (MSTR) and Square Inc. (SQ) have both announced commitments to using Bitcoin, instead of cash, as part of their corporate treasuries. This caused the price to almost double by approximately $24,000- $40,000 in December 2020 – January 2021. In figure 9, we have presented the 30-day forecast of price of Bitcoin, that takes place between 1st January - 29th January 2021.

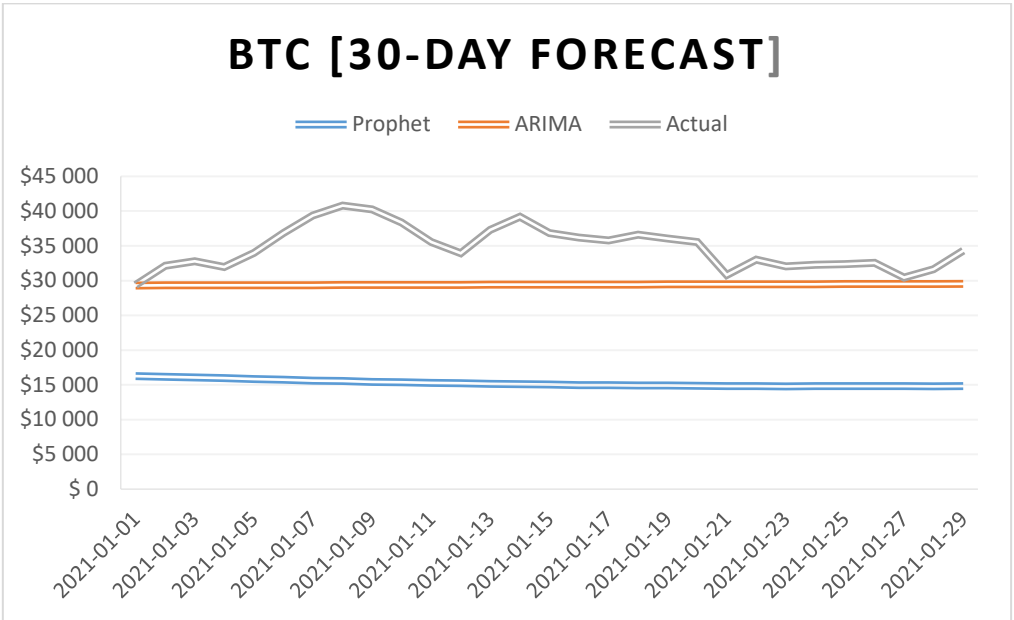

Figure 9 ARIMA(1,1,0) vs Prophet, 30-day forecast

The evaluation of our model's performance of the 30-day forecast of Bitcoin price is presented in Table 10. We can clearly observe that our models performed worse compared to the forecast of Google price once again and confirm that the price movements of the Bitcoin were more unpredictable than Google. The Figure 9, show that none of the models could predict the upswing of the Bitcoin price, as its peaks, 5th to 9th January, thus caused the price to increase by 15,56%. The models deviate to the actual values when price suddenly increases. on 27th January, Several days after the announcement the price decreases and bottoming at $30,433. Where the ARIMA (1,1,0) did the best prediction of $29,518 (see Appendix 1.3).

MODEL	RMSE	PREMSE	MAPE
Prophet	755.59	34.41%	31.35%
ARIMA (1,1,0)	15.13	0.70%	0.00%

Table 10 RMSE table of Bitcoin B

As we have presented before in our evaluation result, we found that both models did better job when predicting prices of Google (4th May – 17th May 2021). It´s easy to understand why when comparing change in price of both assets. Where the largest change in Google price was -3,33%, between 7th – 12th May 2021 (See figure 10),. When on a clear day price of Bitcoin can move 10 times the price of Google. We could not find any announcement that have any significant impact on rational expectation on Google. This suggest that the price of Google next period remains the same.

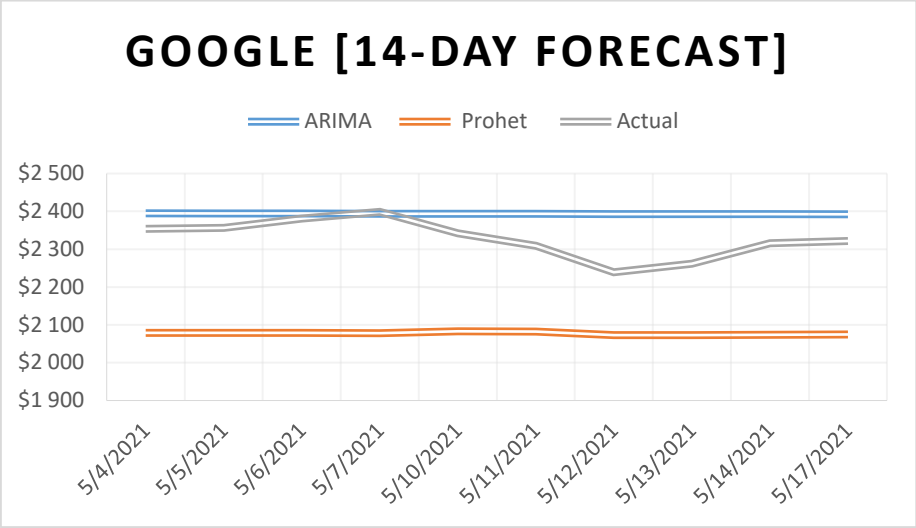

Figure 10 ARIMA (1,1,0) vs Prophet, 14-day forecast

In our evaluation result we found that both models' performing worse when forecasting price of Bitcoin compared to Google, thus price of Bitcoin is more unpredictable and is explained by how announcement significantly affecting the assets price. None of our models were able to keep up when Bitcoin price suddenly changed direction. When Elon musk's announced that Tesla will accept Bitcoin as payment of method when purchasing Tesla cars, caused the price to peak and continuously increasing a short period after the day of the announcement. The upswing was followed by a decline in price when the announcement lost its influencing power and became less relevant. An announcement of this nature affects people rational expectation and thoughts about Bitcoin, such as a step closer to a universal currency. Other entrepreneurs might as well follow Elon musk's lead and make announcement of their own, thus with Bitcoin as method payment could improve sale and generate supernormal profit, due to Bitcoin is not a new service or product but a new method of payment and is similar to when PayPal was introduced in beginning of 19th century. An announcement influencing power is depending on people's expectation and passed experiences and the available information. One reason why the announcement had such an impact is because Bitcoin do not have a known leader where Elon Musk somehow fill that position as a highly influencing entrepreneur. The availability of information is not stable, and it is not limited, thus it is constantly growing as new leaders, networks, platform, groups are coming forth. Based on this, there is moreover incensement for future announcement that will affect the Bitcoin price once again. Where the same pattern will be notified, thus Bitcoin price will decrease or increase based on the nature of the announcement, followed by change in price according to the topicality of the announcement.

Other commodities that are highly influenced by people's expectations are called "meme stocks", commonly used on the famous social platform Reddit and even more during the attribute of GameStop, Oct – Dec 2020. GameStop had hard time with many years of struggle to the new market demands. This is because people's consumption behavior has rapidly changed where most people prefer to buy their games at home rather than over desk. GameStop was depended on regular costumer rather than new once which eventually led to financial problems. Many supporters of GameStop promoted the GME stock on the social platform Reddit, in their attempt to save the company from bankruptcy. Large number of investors reacted to when Wallstreet investors preannounced that the company will not make it. This caused a chain reaction where one group of investors came together. One of the most known groups is "WallStreetBets". They supported the survival of GameStop by investing

and shared their hopes and expectation about the company's future. This led to more people eventually got their attentions through media and other social platforms. The built-up expectation from the magnitude of the announcement caused the GME stock to skyrocket. "So why are shares of the video game retailer up more than 275% so far in 2021? The company can thank a loyal group of investors on Reddit who continue to back the stock even as many others on Wall Street have argued that the shares are overvalued and due for a sharp decline." (La Monica, 2021). This indicate that stocks price may not only necessarily depend on regulations and announcement from powerful people such as Elon Musk, but also from daily investors. Some of the vocabulary used on reddit to confirm this are "Rockets: When someone wants a stock price to skyrocket. or Diamond hands: When a trader is prepared to hold onto their stocks or securities for a long time. Hold the line: Holding on to a stock, even if it goes down in value.

7. Conclusion

We can conclude from our evaluation results that the ARIMA (1,1,0) model show to have better forecasting ability than the Prophet model. When forecasting price of Bitcoin, ARIMA (1,1,0) model was clearly superior to the Prophet model, thus was better to handle uncertainty of Bitcoin future price movements. The uncertainty of the Bitcoins price movements is explained by the evaluations result, where we observed a large difference between the model's performance, thus RMSE was many times higher of both models when forecasting price of Bitcoin compared to Google (GOOG). The highest value of RMSE was estimated of the 30-day forecast of Bitcoin price and strengthen this conclusion.

The uncertainty of future price of Bitcoin is connected to rational expectations and announcement related to Bitcoin and is influencing the Bitcoin price; hence, Elon Musk's announcement 12th May 2021, when he recanted Bitcoin as a method of payment for Tesla cars, thus caused the price to drop notably. While announcement of Bitcoin as an alternative to hedge against pandemic caused the price to rise. The expectation theory suggests that people who believe that the price of Bitcoin will drop will occur, as we presented in our result. The conclusion is based on the analysis of the assets price history, where we did not find any announcement that had significant impact over changes of Google stock price, thus current expectation on Google price remains unchanged and suggest that next period of Google price will be the same. We can conclude from this that it is the uncertainty of Bitcoins price movements rather than the certainty of price movement of Google that explains why the models performance differs.

Although the ARIMA (1,1,0) model had the better forecasting ability according to our evaluation of 14-day forecast of Bitcoin prices. The Prophet model still outperform ARIMA model the last days of the forecast. Nevertheless, none of the model were able to keep up the drop of Bitcoin price presented in the Figure 7 nor the upswing in Figure 9. Although, both models deviate from the actual values of Bitcoin price they contribute with decent forecasts. We can conclude from this, that the evaluation of the model's performance also depends on chosen period and timeframe.

This paper was merely an introduction of how to make forecasts with Facebook Prophet, for more detail interpretations and how to build models, I recommend GitHub and Kaggle. The final word for this paper is dedicated to the model's overall performance which could

be enhanced. In the future we are going to tune our data by using cross- validation and metrics to compare different model to make better forecasts.

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Appendix 1

1.1 Dickey-Fuller table

	Model 1 - constant, no trend				Model 2 - constant, trend			
N	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10
25	-3.724	-3.318	-2.986	-2.633	-4.375	-3.943	-3.589	-3.238
50	-3.568	-3.213	-2.921	-2.599	-4.152	-3.791	-3.495	-3.181
100	-3.498	-3.164	-2.891	-2.582	-4.052	-3.722	-3.452	-3.153
250	-3.457	-3.136	-2.873	-2.573	-3.995	-3.683	-3.427	-3.137
500	-3.443	-3.127	-2.867	-2.570	-3.977	-3.670	-3.419	-3.132
>500	-3.434	-3.120	-2.863	-2.568	-3.963	-3.660	-3.413	-3.128

Table of Dickey-Fuller critical values.

1.2 Forecast Table Bitcoin A

Prophet	ARIMA(1,1,0)	Actual	Date
$44 701	$54 525	$53 191	05/04/2021
$44 657	$54 686	$52 969	05/05/2021
$44 637	$54 847	$55 383	05/06/2021
$44 729	$55 009	$55 322	05/07/2021
$44 714	$55 172	$56 975	05/08/2021
$44 674	$55 335	$56 482	05/09/2021
$44 753	$55 498	$54 071	05/10/2021
$44 764	$55 662	$54 609	05/11/2021
$44 732	$55 826	$49 151	05/12/2021
$44 728	$55 991	$46 980	5/13/2021
$44 839	$56 156	$48 869	5/14/2021
$44 847	$56 322	$46 664	5/15/2021
$44 834	$56 488	$43 963	5/16/2021

$44 941	$56 655	$42 340	5/17/2021

Table of Bitcoin, 14-day Forecast

1.3 Forecast Table Bitcoin B

Prophet	ARIMA (1,1,0)	Actual	Date
$16 257	$29 290	$29 374	2021-01-01
$16 136	$29 310	$32 127	2021-01-02
$16 063	$29 320	$32 782	2021-01-03
$15 952	$29 329	$31 972	2021-01-04
$15 855	$29 337	$33 992	2021-01-05
$15 741	$29 345	$36 824	2021-01-06
$15 627	$29 353	$39 371	2021-01-07
$15 542	$29 362	$40 798	2021-01-08
$15 435	$29 370	$40 255	2021-01-09
$15 382	$29 378	$38 356	2021-01-10
$15 297	$29 386	$35 567	2021-01-11
$15 232	$29 395	$33 923	2021-01-12
$15 153	$29 403	$37 316	2021-01-13
$15 079	$29 411	$39 187	2021-01-14
$15 035	$29 419	$36 825	2021-01-15
$14 971	$29 428	$36 178	2021-01-16
$14 962	$29 436	$35 791	2021-01-17
$14 921	$29 444	$36 630	2021-01-18
$14 899	$29 452	$36 070	2021-01-19
$14 862	$29 460	$35 548	2021-01-20
$14 828	$29 469	$30 826	2021-01-21
$14 823	$29 477	$33 006	2021-01-22
$14 794	$29 485	$32 068	2021-01-23
$14 818	$29 493	$32 289	2021-01-24
$14 808	$29 502	$32 366	2021-01-25
$14 813	$29 510	$32 570	2021-01-26
$14 801	$29 518	$30 433	2021-01-27
$14 789	$29 526	$31 650	2021-01-28
$14 803	$29 534	$34 316	2021-01-29

Table of Bitcoin, 30-day Forecast.

1.4 Forecast Table Google

ARIMA(1,1,0)	Prohet	Actual	Date
$2 395	$2 079	$2 354	5/4/2021
$2 395	$2 079	$2 357	5/5/2021
$2 394	$2 079	$2 381	5/6/2021
$2 394	$2 078	$2 399	5/7/2021
$2 394	$2 083	$2 342	5/10/2021
$2 393	$2 082	$2 309	5/11/2021
$2 393	$2 073	$2 239	5/12/2021
$2 393	$2 073	$2 262	5/13/2021
$2 393	$2 074	$2 316	5/14/2021
$2 392	$2 074	$2 321	5/17/2021

Table of Google, 14- day forecast.

1.5 AIC & BIC estimation of Bitcoin closing price

Residual Diagnostics	
Number of Residuals	2188
Number of Parameters	1
Residual df	2187
Adjusted Residual Sum of Squares	3,346
Residual Sum of Squares	3,342
Residual Variance	,002
Model Std. Error	,039
Log-Likelihood	3987,745
Akaike's Information Criterion (AIC)	-7971,491
Schwarz's Bayesian Criterion (BIC)	-7960,800

ARIMA(0,1,0)

Residual Diagnostics

Number of Residuals	2188
Number of Parameters	2
Residual df	2186
Adjusted Residual Sum of Squares	3,344
Residual Sum of Squares	3,341
Residual Variance	,002
Model Std. Error	,039
Log-Likelihood	3988,248
Akaike's Information Criterion (AIC)	-7972,497
Schwarz's Bayesian Criterion (BIC)	-7961,115

ARIMA (1,1,0)

Residual Diagnostics

Number of Residuals	2188
Number of Parameters	3
Residual df	2185
Adjusted Residual Sum of Squares	3,344
Residual Sum of Squares	3,341
Residual Variance	,002
Model Std. Error	,039
Log-Likelihood	3988,262
Akaike's Information Criterion (AIC)	-7970,524
Schwarz's Bayesian Criterion (BIC)	-7953,452

ARIMA (1,1,1)

1.6 AIC & BIC estimation of Google closing price

Residual Diagnostics

Number of Residuals	1593
Number of Parameters	1
Residual df	1592
Adjusted Residual Sum of Squares	,459
Residual Sum of Squares	,459
Residual Variance	,000
Model Std. Error	,017
Log-Likelihood	4231,937
Akaike's Information Criterion (AIC)	-8461,874
Schwarz's Bayesian Criterion (BIC)	-8456,501

ARIMA(0,1,0)

Residual Diagnostics

Number of Residuals	1593
Number of Parameters	2
Residual df	1591
Adjusted Residual Sum of Squares	,456
Residual Sum of Squares	,456
Residual Variance	,000
Model Std. Error	,017
Log-Likelihood	4237,252
Akaike's Information Criterion (AIC)	-8470,503
Schwarz's Bayesian Criterion (BIC)	-8459,756

ARIMA(1,1,0)

Residual Diagnostics

Number of Residuals	1593
Number of Parameters	3
Residual df	1590
Adjusted Residual Sum of Squares	,456
Residual Sum of Squares	,456
Residual Variance	,000
Model Std. Error	,017
Log-Likelihood	4237,283
Akaike's Information Criterion (AIC)	-8468,567
Schwarz's Bayesian Criterion (BIC)	-8452,447

ARIMA(1,1,1)