The Effect of the COVID-19 Pandemic on the Correlation Between Cryptocurrency Prices (Bitcoin, Ethereum, Litecoin, etc.) and Currencies Traded on the Foreign Exchange Market (USD, JPY, EUR, etc)

Hunter Baxter and Hannah Yoon

Introduction

COVID-19

Since its first report in the city of Wuhan, China in December, 2019, coronavirus Disease 2019 (COVID-19) has posed unprecedented challenges to the health, economic, environments, and social domains. COVID-19 was declared as a pandemic by the World Health Organization on March 11th, 2020 due to its fast speed and large scale of transmission (Dos Santos, 2020). Not only did the pandemic lead to dramatic loss of human life, but the economic and social disruptions caused by COVID-19 have drastically changed the lives of every human being on the planet. Most countries have imposed social distancing policies and travel restrictions. Industries are shut down to low mobility and millions of people have lost their jobs. The International Monetary Fund (IMF) has estimated a 3% decline in global economic growth in 2020. Most economies in the advanced economy group are expected to contract in 2020, including the US, Japan, the UK, Germany, France, Italy and Spain by 5.9%, 5.4%, 6.5%, 7.0%, 7.2%, 9.1%, and 8.0% respectively (Mofijur et al., 2021).

Cryptocurrencies

A cryptocurrency is an encrypted digital medium of exchange that is traditionally decentralized, but not exclusively. The first cryptocurrency to gain notoriety was Bitcoin (BTC). Bitcoin is a peer-to-peer digital cash that uses cryptographic proof instead of trust to avoid having to go through financial institutions (Nakamoto, 2008). In addition, Bitcoin can be seen as a hybrid between a fiat currency and commodity due to its circulation mechanisms. However, despite being designed to be used as a day-to-day currency for many small exchanges, some view Bitcoin as a speculative asset (Baur, 2018).

Main Research Question

The main research objective is to investigate the behavior of cryptocurrency and foreign exchange markets during the COVID-19 pandemic to see if there are any insights into the question: is Bitcoin, and cryptocurrencies as a whole, more of a currency or speculative asset?

Data Collection and Processing

Cryptocurrencies and Foreign Exchange Market Data Collection

This project uses cryptocurrency and foreign exchange market data obtained from the Polygon.io REST API. Polygon.io is a data vendor that offers real-time and historical data on the stock market, foreign exchange, and cryptocurrency markets. The data was originally in the form of a JSON document containing information about the status and results of the request. After processing, the data is in the form of a new line separated JSON document with the schema described in Table 1. Each JSON blob represents one "tick" of data at a one minute resolution. This conversion was necessary in order to utilize google collab and spark if it ever became necessary. A list of the 15 largest market cap cryptocurrencies from Yahoo! Finance determined the list of cryptocurrencies used. Out of these currencies, Polygon.io had data available for 12, which are listed in Table 2. After constructing a rough ordering of the most traded currencies per continent, the top five currencies were selected, listed in Table 3. In total, there were 37 symbols used, which resulted in 48.16 million data points total.

Field Name	Field Description
p	The exchange symbol that an item is traded under.
t	The Unix Msec timestamp for the start of the aggregate window.
v	The trading volume of the symbol in the given time period.
o	The open price for the symbol in the given time period.
c	The close price for the symbol in the given time period.
h	The highest price for the symbol in the given time period.
l	The lowest price for the symbol in the given time period.
n	The number of transactions in the aggregate window.

Table 1. cryptocurrency and foreign exchange market data from Polygon.io

Symbol	Name	Symbol	Name
BTCUSD	Bitcoin USD	LTCUSD	Litecoin USD
ETHUSD	Ethereum USD	LINKUSD	ChainLink USD
USDTUSD	Tether USD	USDCUSD	USDCoin USD
BNBUSD	BinanceCoin USD	BCHUSD	BitcoinCash USD
ADAUSD	Cardano USD	XLMUSD	Stellar USD
XRPUSD	XRP USD	DOGEUSD	Dogecoin

Table 2. Cryptocurrencies Used

Symbol	Currency	Country	Considered Continent
EURUSD	Euro	European Union	Global*
AUDUSD	Australian Dollar	Australia	Global*
NZDUSD	New Zealand Dollar	New Zealand	Global*
CADUSD	Mexican Peso	Mexico	North America
MXNUSD	Canadian Dollar	Canada	North America
BRLUSD	Brazillian Real	Brazil	South America
ARSUSD	Argentine Peso	Argentina	South America
BOBUSD	Bolivian Bolíviano	Bolivia	South America
CLPUSD	Chilean Peso	Chile	South America
COPUSD	Colombian Peso	Columbia	South America
GBPUSD	Pound Sterling	Great Britain	Europe
SEKUSD	Swedish Krone	Sweden	Europe
CHFUSD	Swiss Franc	Switzerland	Europe
HUFUSD	Hungarian Forint	Hungary	Europe
RUBUSD	Russian Ruble	Russia	Europe
JPYUSD	Japanese Yen	Japan	Asia

CNYUSD	Chinese Yuan	China	Asia
HKDUSD	Hong Kong Dollar	Hong Kong	Asia
KRWUSD	South Korean Won	South Korea	Asia
INRUSD	Indian Rupee	India	Asia
ZARUSD	South African Rand	South Africa	Africa
LYDUSD	Libyan Dinar	Libya	Africa
TNDUSD	Tunisian Dinar	Tunisia	Africa
MADUSD	Morrocan Dirham	Morocco	Africa
GHSUSD	Ghanaian Cedi	Ghana	Africa

Table 3. Foreign Exchange Currencies Used

COVID-19 Data Collection

The COVID-19 dataset was obtained from Kaggle in the form of csv files (Assaker, 2021). Created by Joseph Assaker, the dataset is updated periodically to contain the most up-to-date information by scraping data from worldometers.info, however the version that was used in this paper contains data upto April 24th, 2021. A total of 218 countries are represented in the dataset, in which all countries have daily records collected from February 15th, 2020 until April 24th, 2021 (435 recordings per country) with the exception of China, which has daily records collected from January 22nd, 2020 until April 24th, 2021. For the purpose of maintaining consistency across countries as well as setting a common end date with the cryptocurrency and foreign exchange currency pair data, the time range was limited such that only data from February 15th, 2020 to April 1st, 2021 were used for all countries. Two csv files are included in this dataset: "worldometer_coronavirus_summary_data.csv" and "worldometer_coronavirus_daily_data.csv". The daily data of covid-19, saved in "worldometer_coronavirus_daily_data.csv", has 7 columns which are described in detail in Table 4. From the summary data, saved in "worldometer_coronavirus_summary_data.csv", only the country and continent columns were examined for the purpose of saving the continent value for each country.

Column Name	Column Description
date	The date of observation of the row's data in 'YYYY-MM-DD' format
country	The country in which the row's data was observed

cumulative_total_cases	The cumulative number of confirmed cases as of the row's date, for the row's country
daily_new_cases	The daily new number of confirmed cases on the row's date, for the row's country
active_cases	The number of active cases (i.e., confirmed cases that didn't recover nor die) on the row's date, for the row's country
cumulative_total_deaths	The cumulative number of confirmed deaths as of the row's date, for the row's country
daily_new_deaths	The daily new number of confirmed deaths on the row's date, for the row's country

Table 4. List of columns in the daily COVID-19 data and the description for each column (Assaker, 2021)

InfluxDB

Time series databases (TSDB) are databases optimized for storing and manipulating time series data. Time series data is when there is a dependency between time and the values, and thus exists a pattern within the values observed over time. Among various TSDBs, InfluxDB is considered to be the most widely used TSDB. It is an open-source, schema-less TSDB which offers SQL-like query languages. In a InfluxDB database, there is always a time column, tag columns, and field columns that contain the measurements. The advantages of InfluxDB over other TSDBs is that (1) each field is sequentially organized on the disk for blocks of time, which significantly decreases the time it takes to calculate aggregates on a single field, (2) there is no limit to the number of tags and fields that can be used and (3) it supports data types other than float64, which allows users to encode additional metadata along with the time series (Zehra, 2017). Thus, InfluxDB was selected to store and analyze the cryptocurrencies, foreign exchange currency pairs, and COVID-19 data.

For the COVID-19 data, the time column was set as the 'date' column of the daily COVID-19 data and the field columns were set as the remaining six columns (country, cumulative_total_cases, daily_new_cases, active_cases, cumulative_total_deaths, daily_new_deaths) of the daily COVID-19 data. The tag value for each measurement was set equal to the continent in which the country of measurement resides in, obtained from the summary COVID-19 data. Tags are indexed in InfluxDB which makes queries on tags fast and performant. Thus, the decision to make continents as tags was made in order to fasten the process of grouping countries based on similar COVID-19 related trends and perform queries on groups instead of looking at the data for all countries individually. Additionally, the fact that not all corresponding currency data for the 218 countries in the COVID-19 dataset was obtained and that multiple groups of countries share the same currency (for example, most countries in Europe use EURO), made grouping countries by continents an effective solution for finding the correlation between currency and COVID-19.

For the cryptocurrency and foreign exchange data, the time column was set as a time conversion of ‘t’ (unix time in milliseconds) of our data. The reasoning behind this direct conversion will be discussed in the discussion section. The remaining seven fields (‘p’, ‘v’, ‘o’, ‘c’, ‘h’, ‘l’, ‘n’) of a tick of data were selected as the field columns. The tag value for each measurement was set equal to the symbol name of an object. Using pair names as a tag allows us to query the database for any given currency pair quickly.

InfluxDB also has many conveniently defined technical analysis tools. In particular, we used triple exponential moving average and moving average, but there were more sophisticated ones catered to financavailable if we felt it was necessary.

Analysis and Results

Query 1: Plot cryptocurrency price changes, and currency price changes by continent

We used a 7-day triple exponential moving average function grouped by half days to plot the currencies. We chose to do this because we account for any potential differences in activity in Asia versus North America. We decided on triple exponential smoothing because it weights recent data points more than a standard moving average and responds more quickly to price changes (which reduces lag).

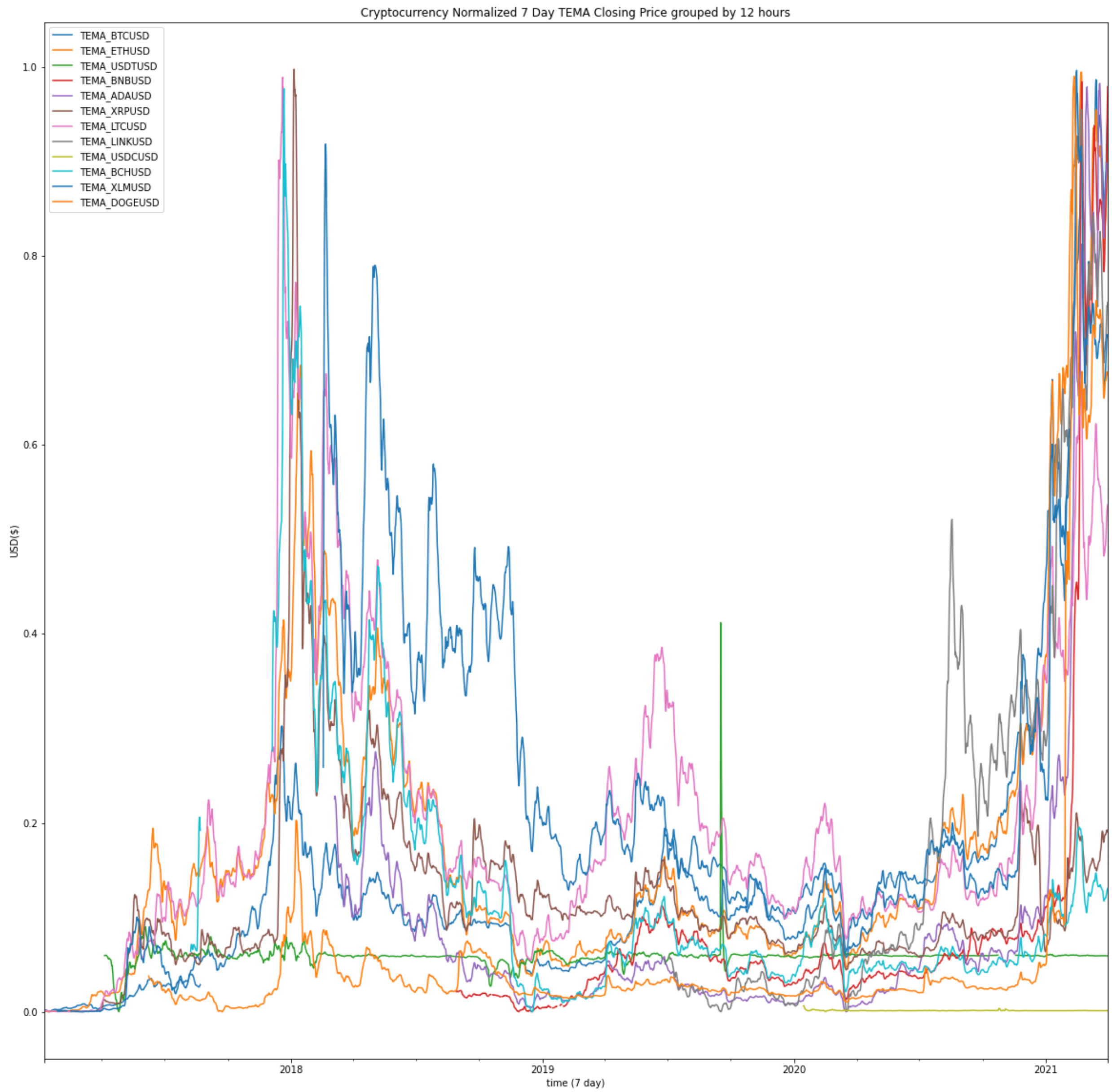

Figure 1. The normalized cryptocurrency closing price changes

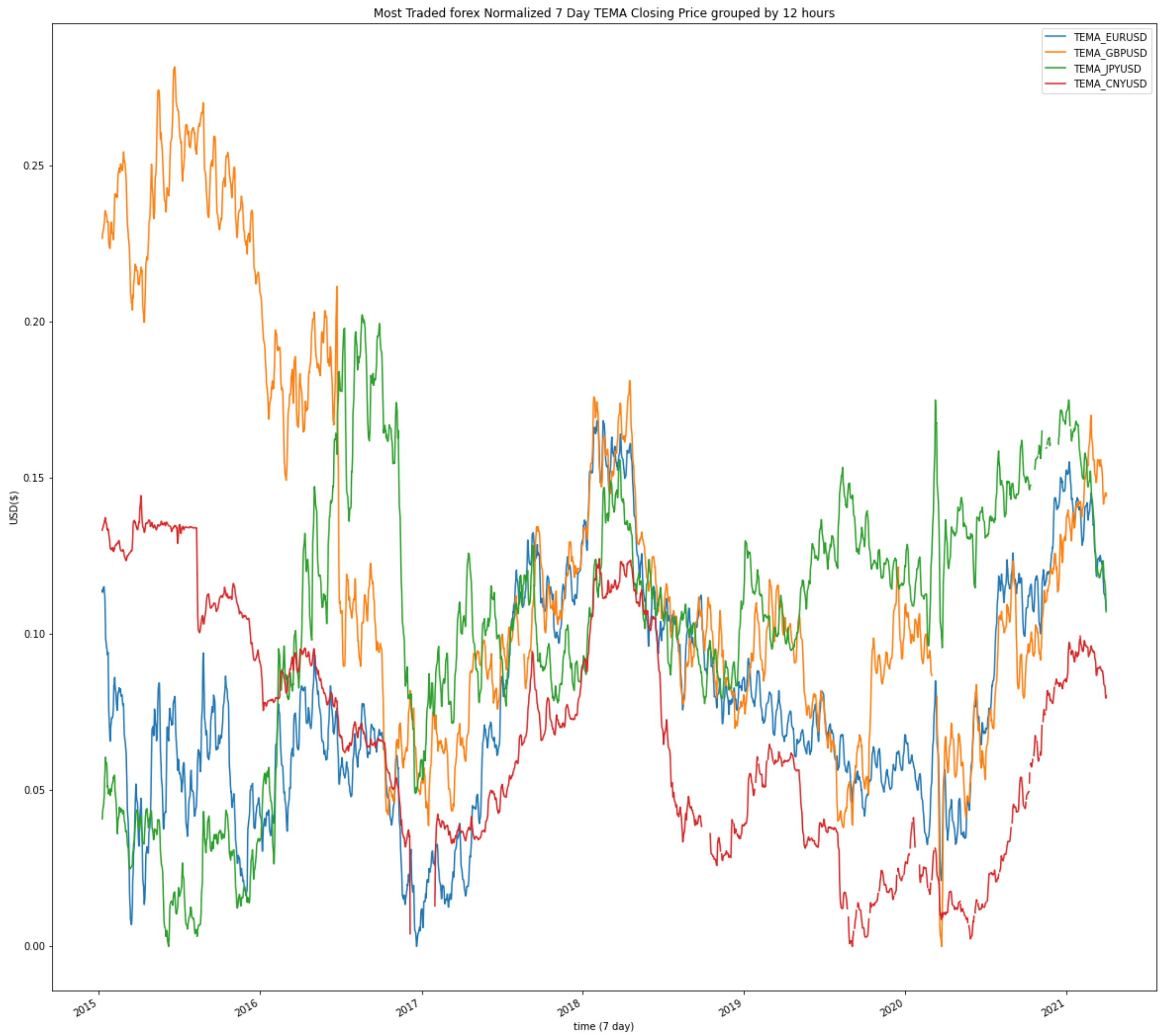

Figure 2. The normalized closing price changes for the most traded currencies

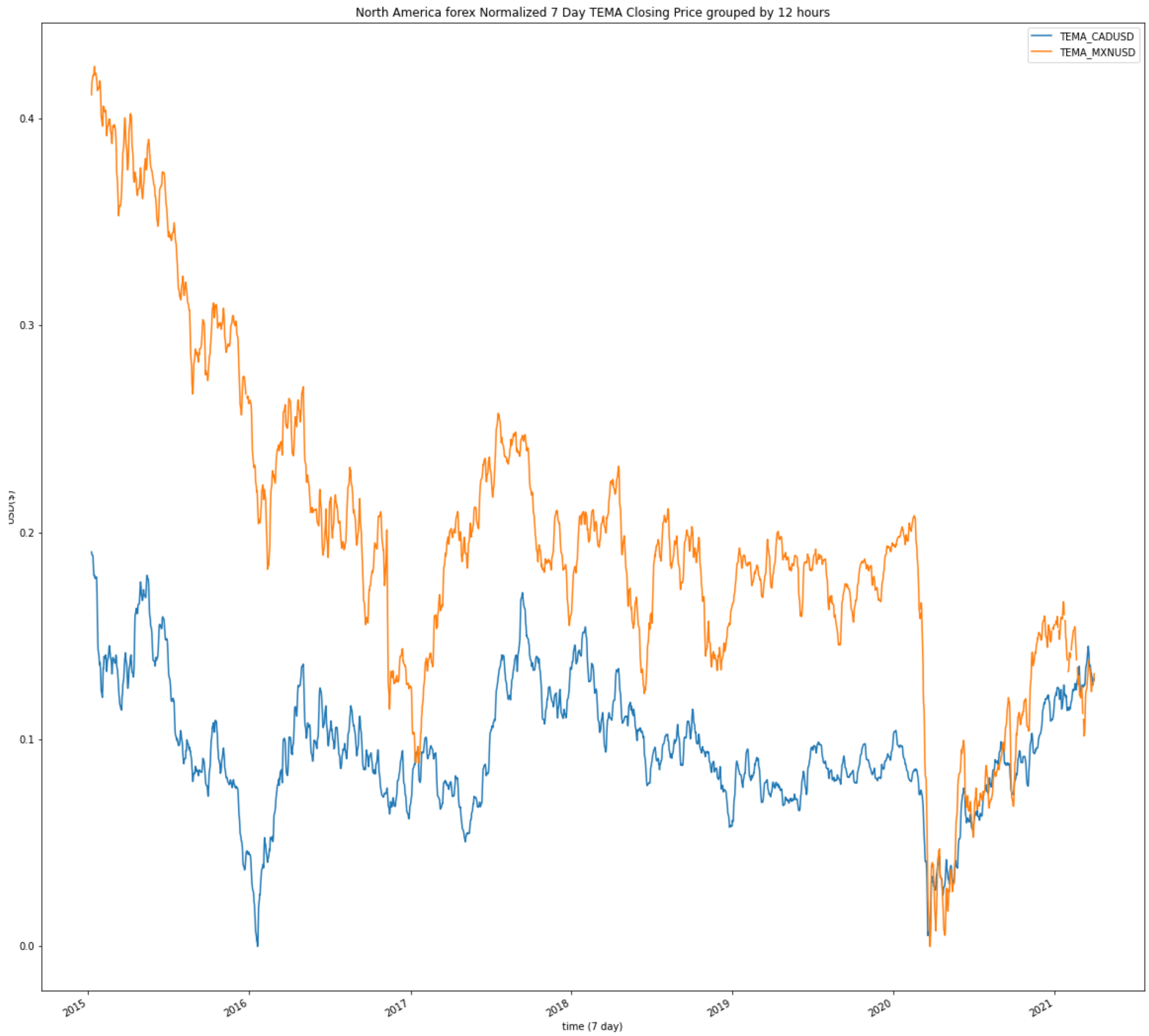

Figure 3. The normalized closing price changes for currencies in North America

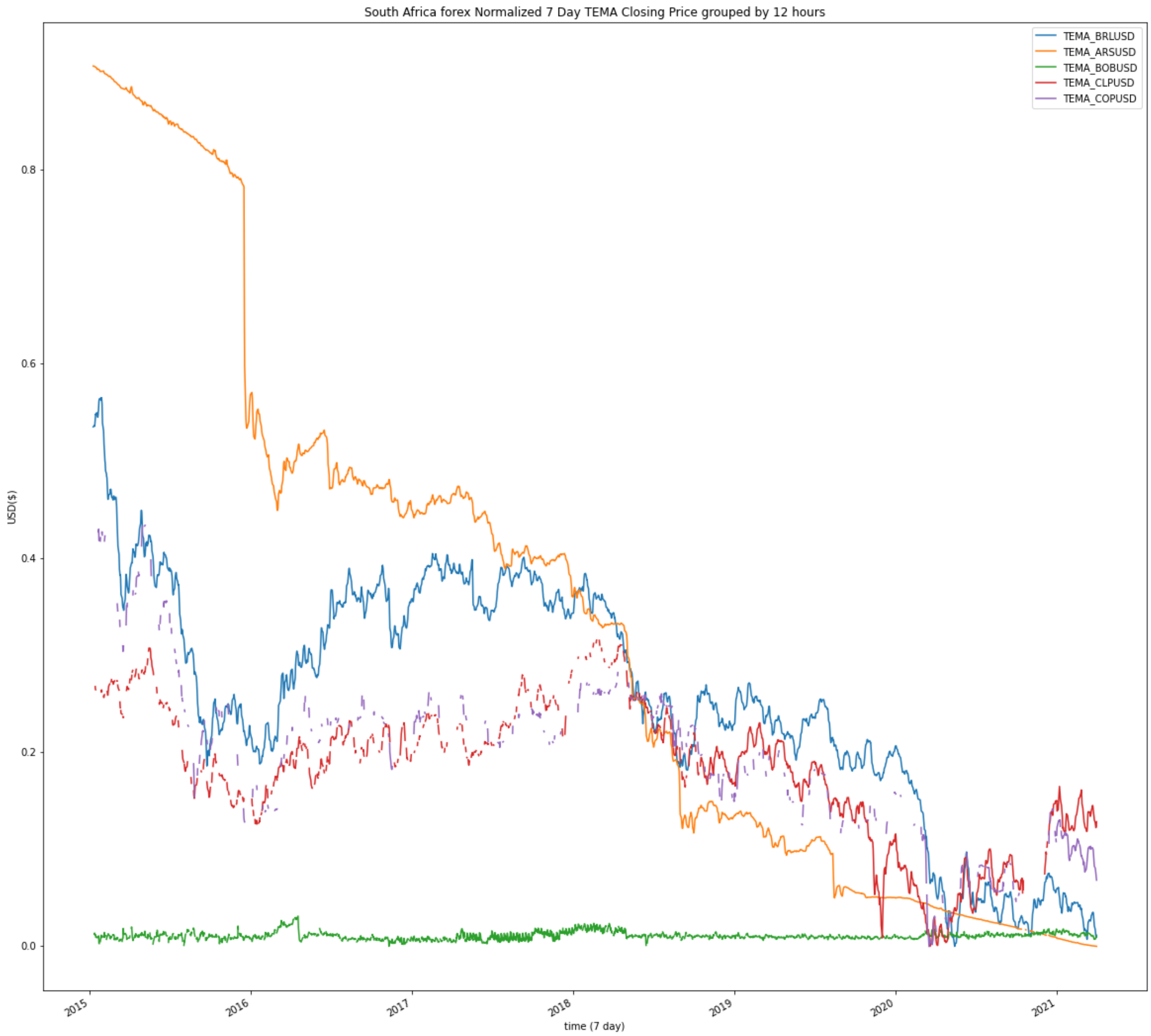

Figure 4. The normalized closing price changes for currencies in South America

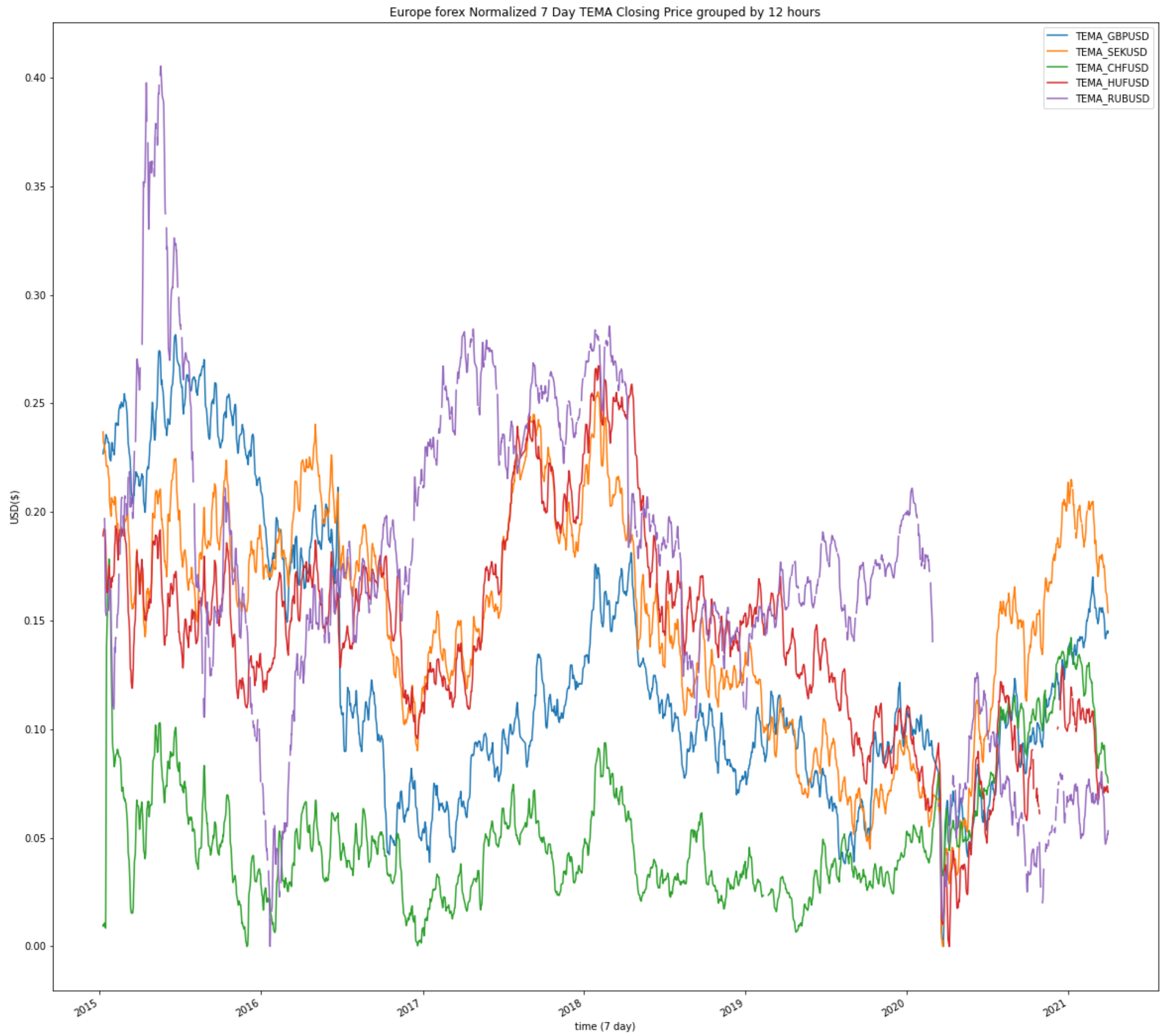

Figure 5. The normalized closing price changes for currencies in Europe

Figure 6. The normalized closing price changes for currencies in Africa

Figure 7. The normalized closing price changes for currencies in Asia

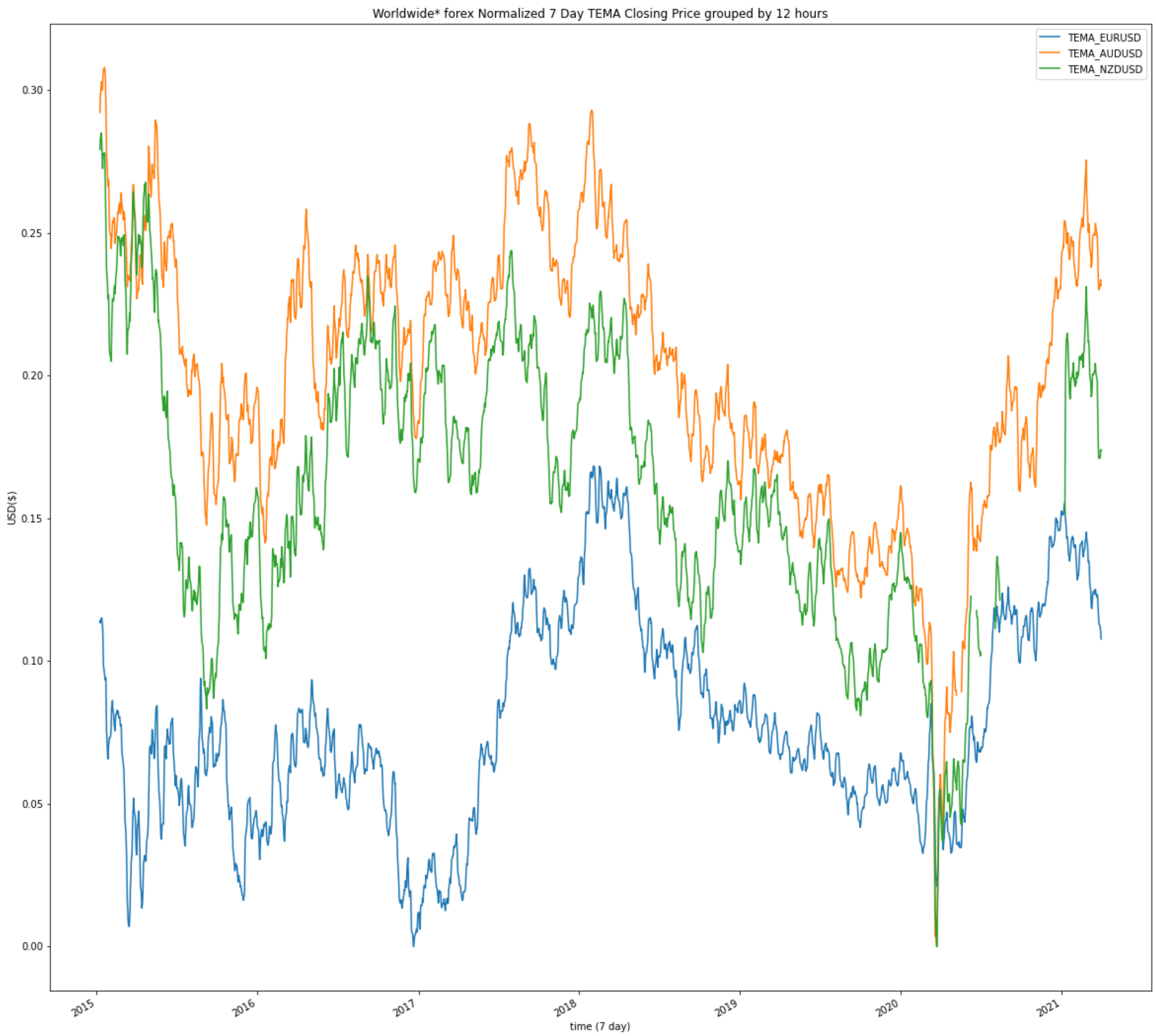

Figure 8. The normalized closing price changes for currencies in worldwide country group

Query 2: Finding correlation between cryptocurrencies

In order to get a better understanding of the relationships between cryptocurrencies, we wanted to find out how correlated each symbol was. This is important because if most cryptocurrencies are correlated with Bitcoin, then it may be a sign that Bitcoin dictates the direction of the cryptocurrency market.

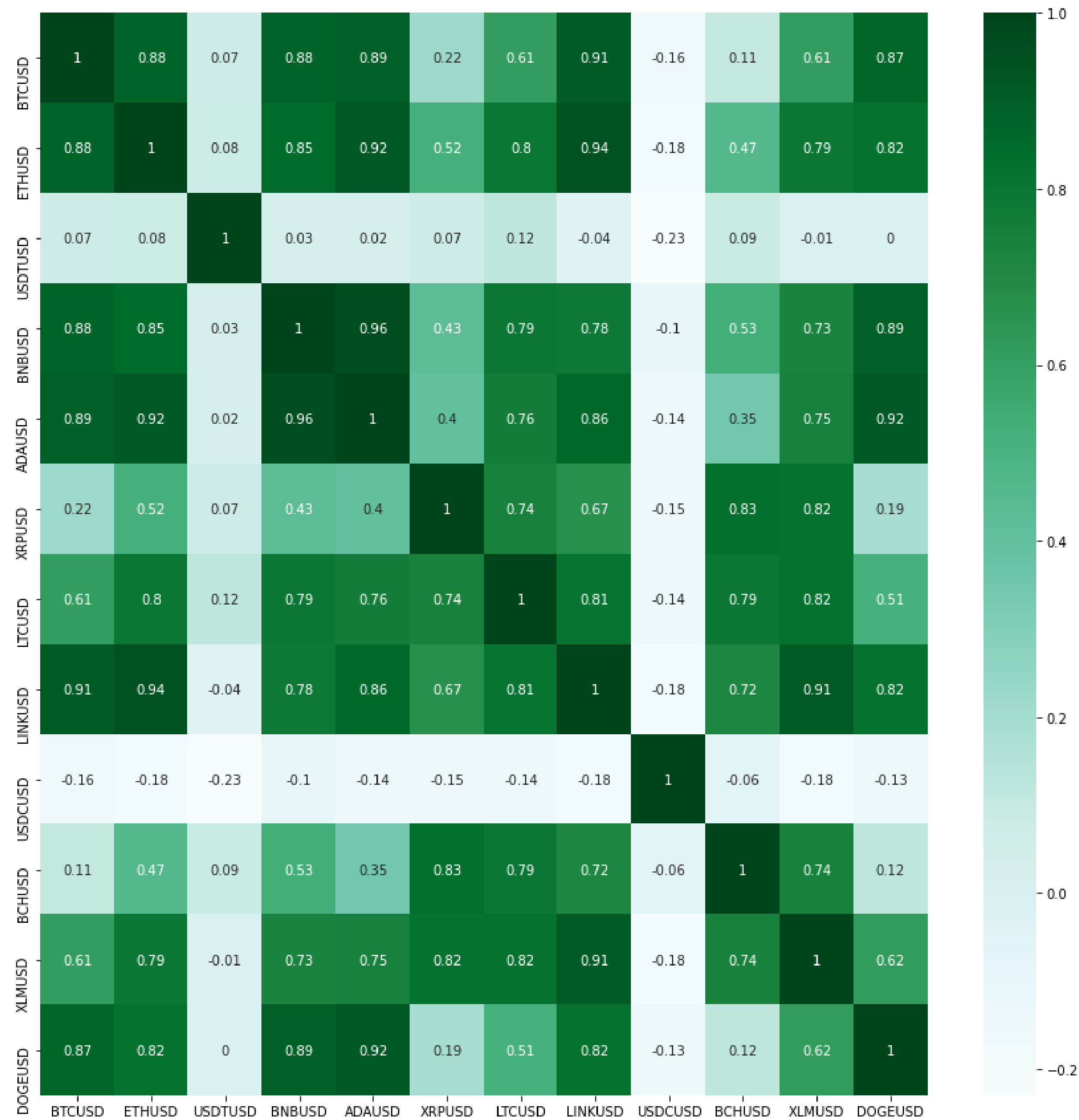

Figure 9. Heatmap of the correlation between cryptocurrencies

2019	BTCUSD	2020	BTCUSD	2021	BTCUSD
XLMUSD	-0.225568	**USDTUSD**	-0.124267	**USDTUSD**	-0.408816
XRPUSD	0.044399	**USDCUSD**	-0.092902	**USDCUSD**	0.369350
USDTUSD	0.125715	**BCHUSD**	0.263490	**BCHUSD**	0.661427
ADAUSD	0.200417	**LINKUSD**	0.702146	**XLMUSD**	0.767974
LINKUSD	0.281188	**XRPUSD**	0.740955	**LINKUSD**	0.778470
LTCUSD	0.609954	**DOGEUSD**	0.768400	**DOGEUSD**	0.794334
DOGEUSD	0.668788	**ADAUSD**	0.787486	**XRPUSD**	0.827258
BNBUSD	0.753330	**BNBUSD**	0.829880	**ETHUSD**	0.850917
ETHUSD	0.756567	**XLMUSD**	0.840042	**LTCUSD**	0.890560
BCHUSD	0.764772	**LTCUSD**	0.857508	**ADAUSD**	0.912963
BTCUSD	1.000000	**ETHUSD**	0.939104	**BNBUSD**	0.939642
USDCUSD	nan	**BTCUSD**	1.000000	**BTCUSD**	1.000000

Figure 10. Cryptocurrency symbols correlation with Bitcoin in ascending order

Query 3: Plot COVID-19 cumulative total cases using 3 days average of each continent

To better understand the effect of COVID-19 on cryptocurrencies and foreign exchange currencies, we visualized the cumulative total cases of COVID-19 grouped and averaged by continents (Figure #). There were six continents that had data for at least one country to represent the continent: (1) Africa, (2) Asia, (3) Australia/Oceania, (4) Europe, (5) North America and (6) South America. In order to avoid any empty values causing a gap in the daily plots, we averaged the daily data by 3 day intervals.

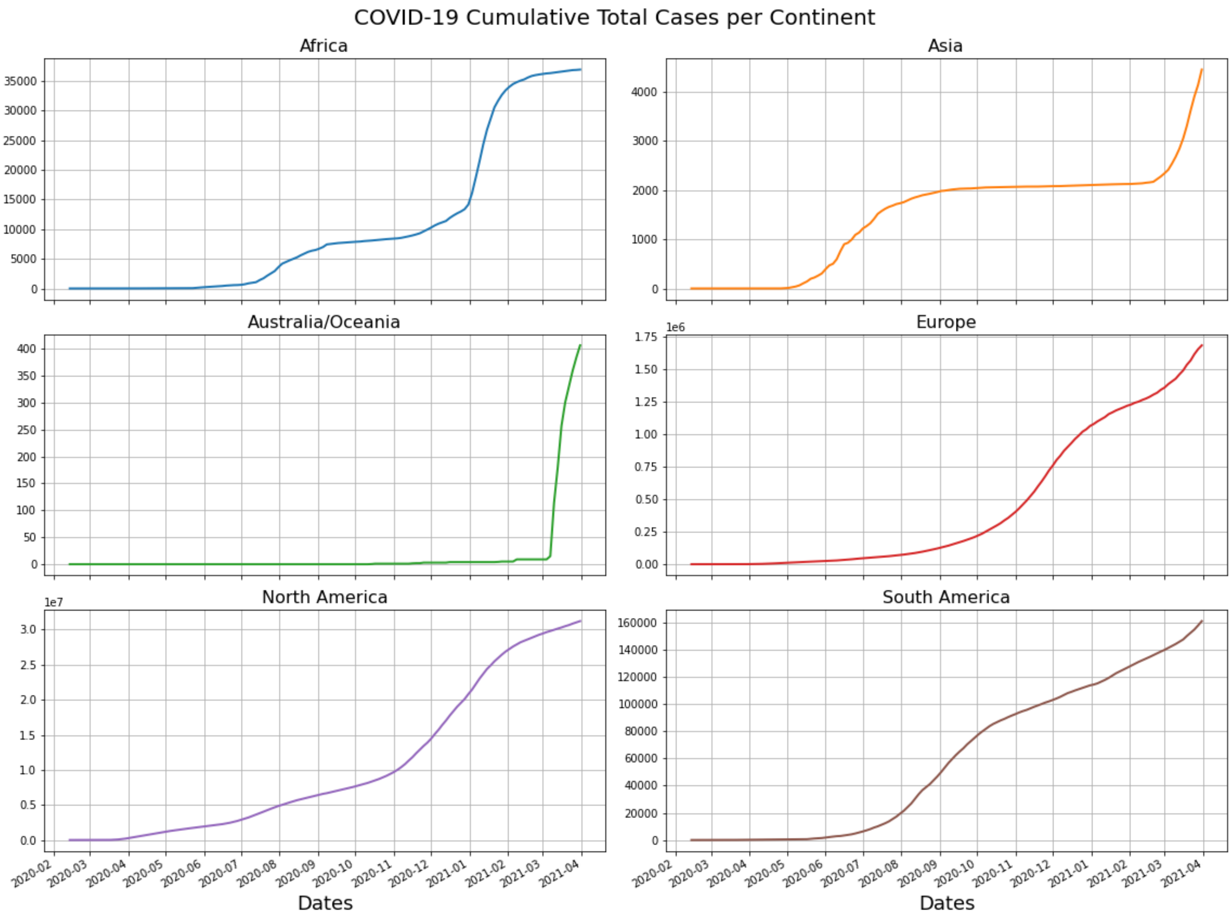

Figure 11. The cumulative total cases of COVID-19 grouped by continent

Query 4: Correlation between daily deaths/cases and the volatility of a currency

Originally, we thought that there might be a correlation between the volatility of the US currency and the amount of COVID-19 cases or deaths. We thought this might occur due to the economic decline that followed COVID-19, but we did not find any consistent high correlations with the US dollar.

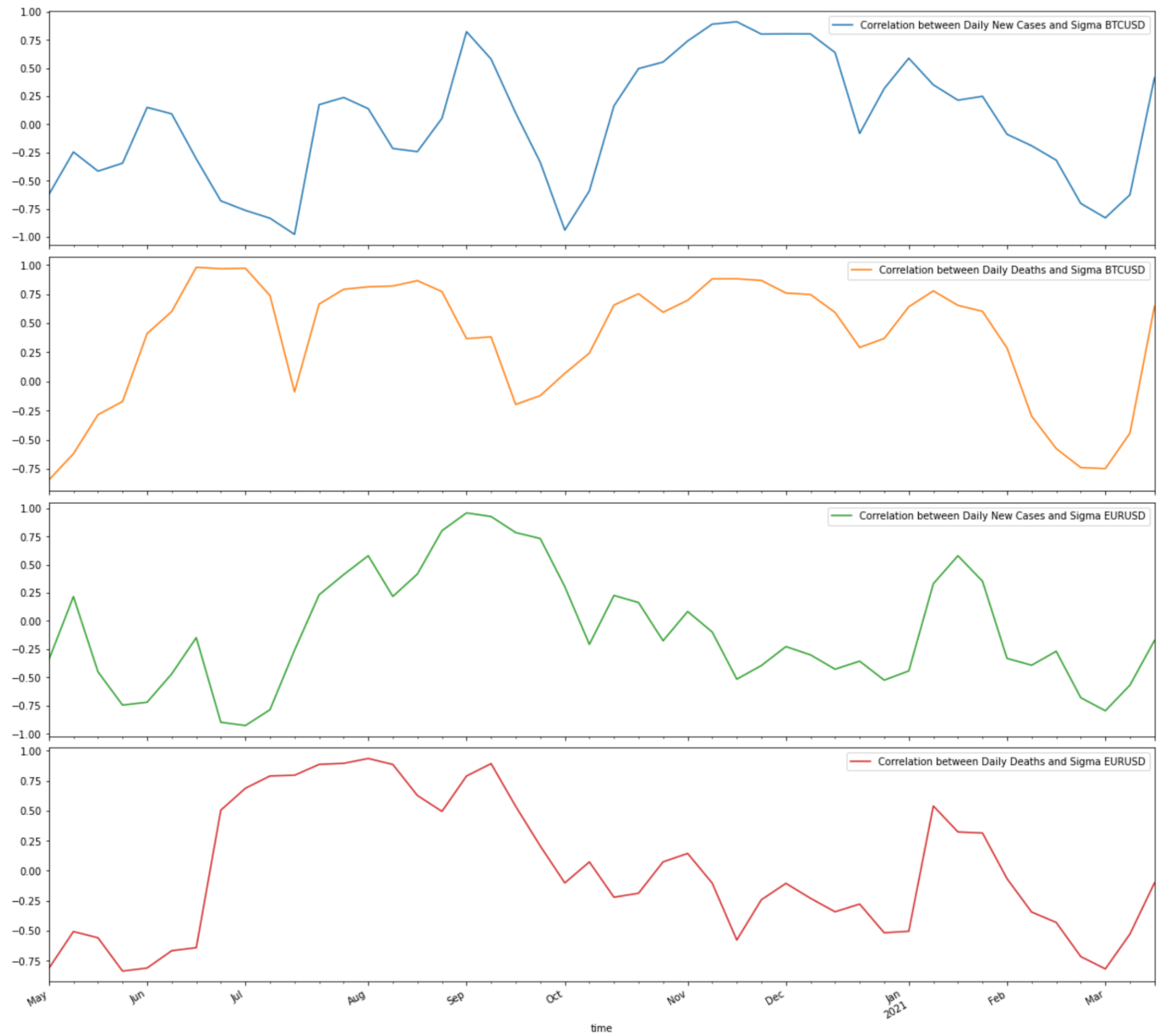

Figure 12. Rolling Correlations between daily new cases and standard deviation of Bitcoin closing price, daily deaths and standard deviation of Bitcoin closing price, daily new cases and standard deviation of EURUSD, and daily deaths and standard deviation of EURUSD

Query 5: Correlation of COVID-19 daily cases and cryptocurrency, foreign exchange currency price change

The correlations between COVID-19 daily new cases of the USA and the currency prices of bitcoin (BTCUSD) and four foriegn exchange currencies (EURUSD, GBPUSD, JPYUSD, CNYUSD) were analyzed using rolling time windows. First, the four currencies, along with bitcoin, were selected according to the list of most traded currencies provided by the Bank for International Settlements (Bank for International Settlements, 2019). The values for the daily new cases of the USA and daily closing prices of the five currencies were averaged by 7 day intervals to avoid any gaps in the data caused by consecutive empty values. There was a gap in the JPYUSD data points, due to consecutively empty values for a period longer than 7 days.Then a rolling time window of 8 data values(8 weeks) was used to find the correlation between the USA COVID-19 daily new cases and currency closing prices for the short 8 weeks windows, where the windows rolled through the data plot with a 6 week overlap (Figures 13,15,17,19,21).

While examining the rolling correlation plots, there was a shift in correlation observed in all of the five currencies examined, in which the correlation starts as a negative correlation in September 2020, starts to increase towards positive correlation, continuing until November 2020, in which the shift stops, and the correlation value stays constantly high for a certain period. Through this observation, it was hypothesized that there is a delayed correlation between COVID-19 and currency closing prices, such that an increase in the COVID-19 daily new cases in the USA would also cause an increase in currency closing prices, however the effect becomes apparent after approximately two months.

To test this hypothesis, the correlation between the USA COVID-19 daily new cases and currency closing prices was analyzed once more, but with shifted currency closing prices. Four starting data points were eliminated from the currency closing prices data, which thus shifted the data to the left by a month. When the rolling correlation was plotted between the shifted closing prices and COVID-19 daily cases, the correlation values increased significantly and remained high for a long period of time for the currencies EURUSD and GBPUSD (Figures 14, 16). For the correlation between COVID-19 and bitcoin closing prices, there was an outlier in late September 2020, which broke the continuation of high correlation values into two short time intervals, however eliminating that outlier, the change in correlation values showed the same pattern as EURUSD and GBPUSD (Figure 22). There was no observable improvement in the correlation values between COVID-19 and CNYUSD and JPYUSD (Figures 18, 20). Thus, the conclusion that COVID-19 daily new cases in the USA has a delayed impact on the closing prices of several currencies.

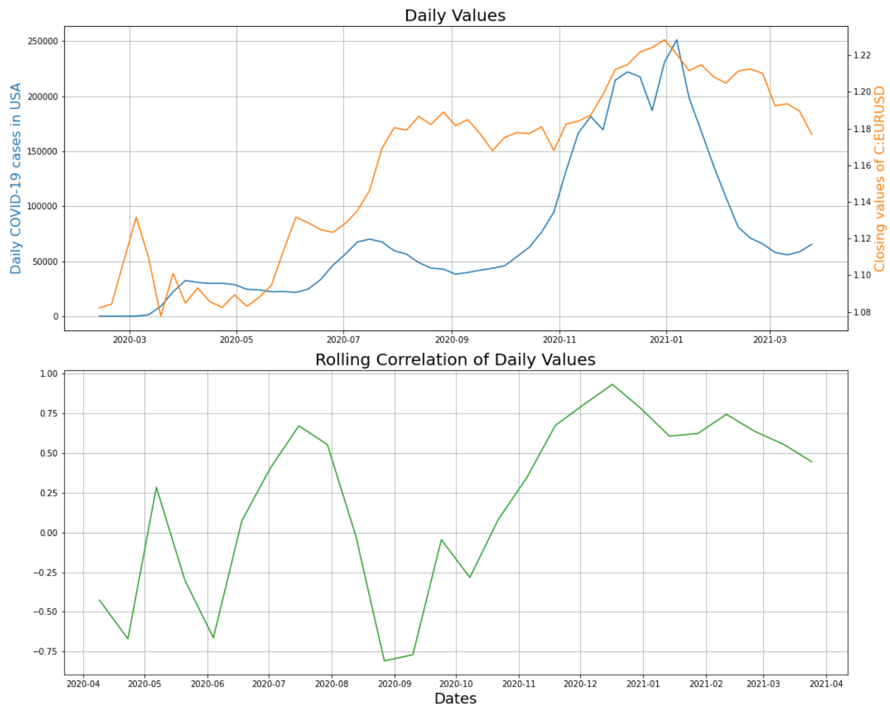

Figure 13. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair EURUSD.

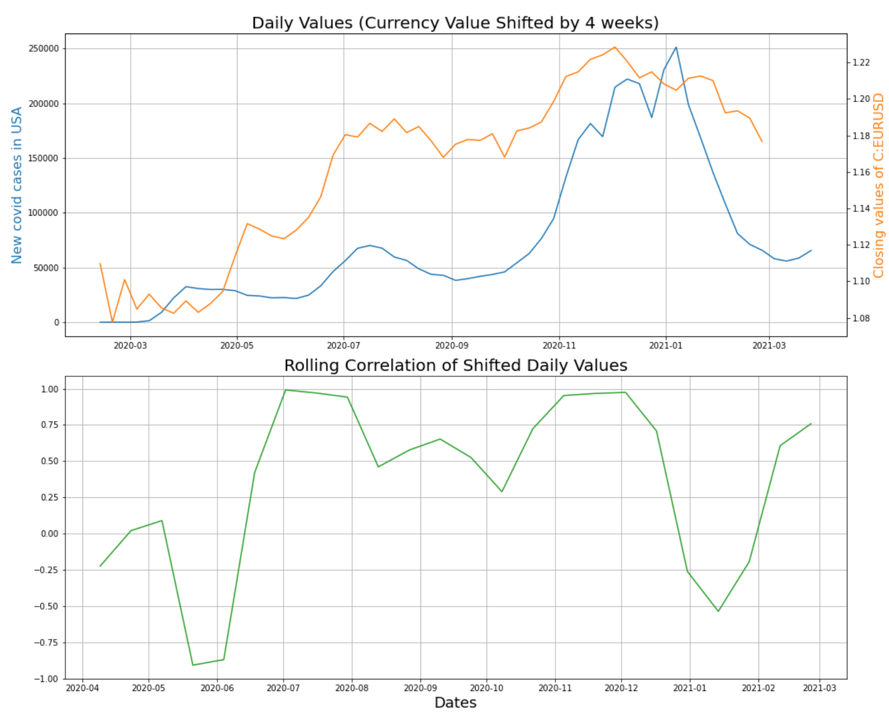

Figure 14. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair EURUSD shifted by a month to the left.

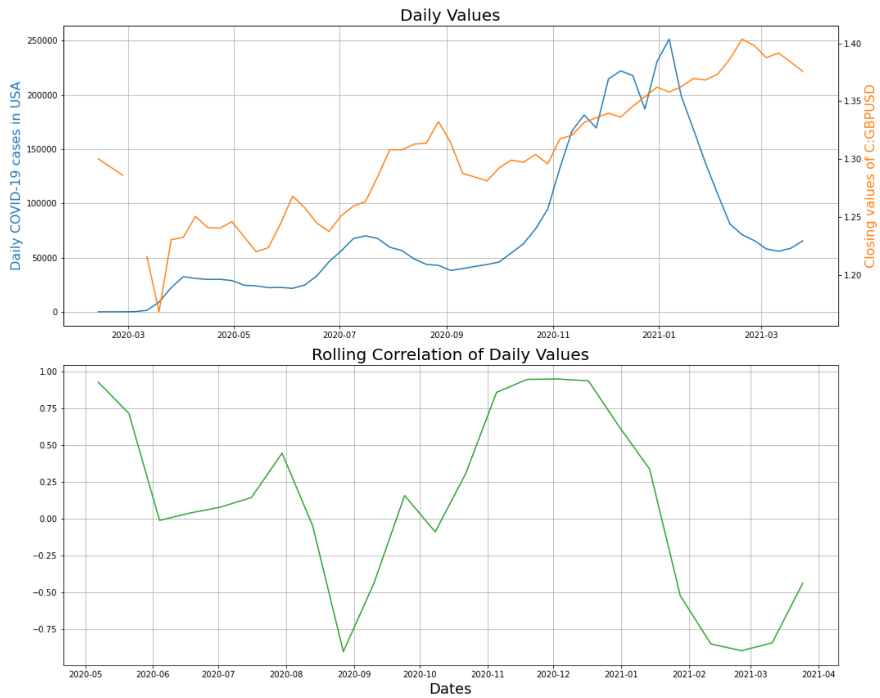

Figure 15. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair GBPUSD.

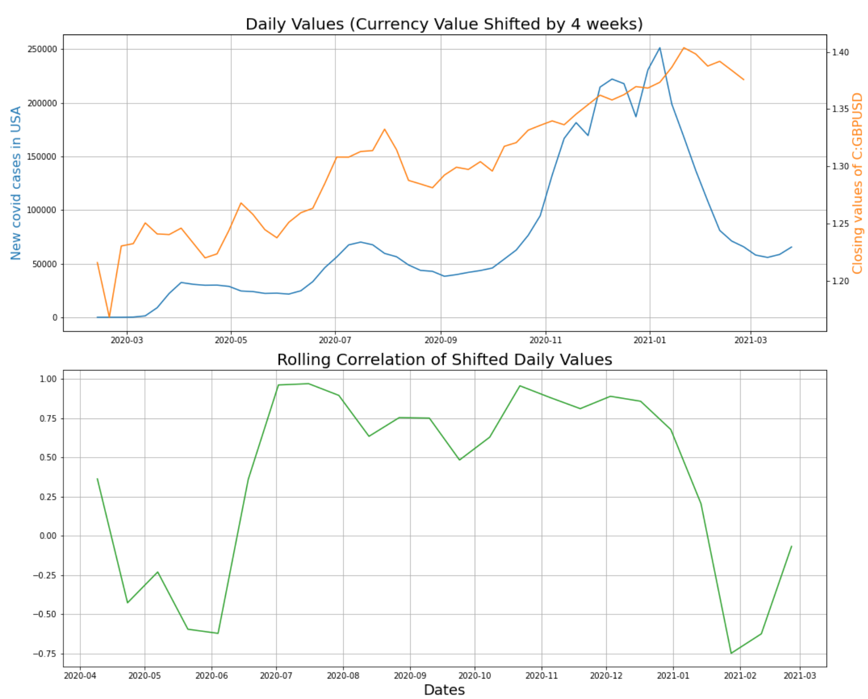

Figure 16. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair GBPUSD shifted by a month to the left.

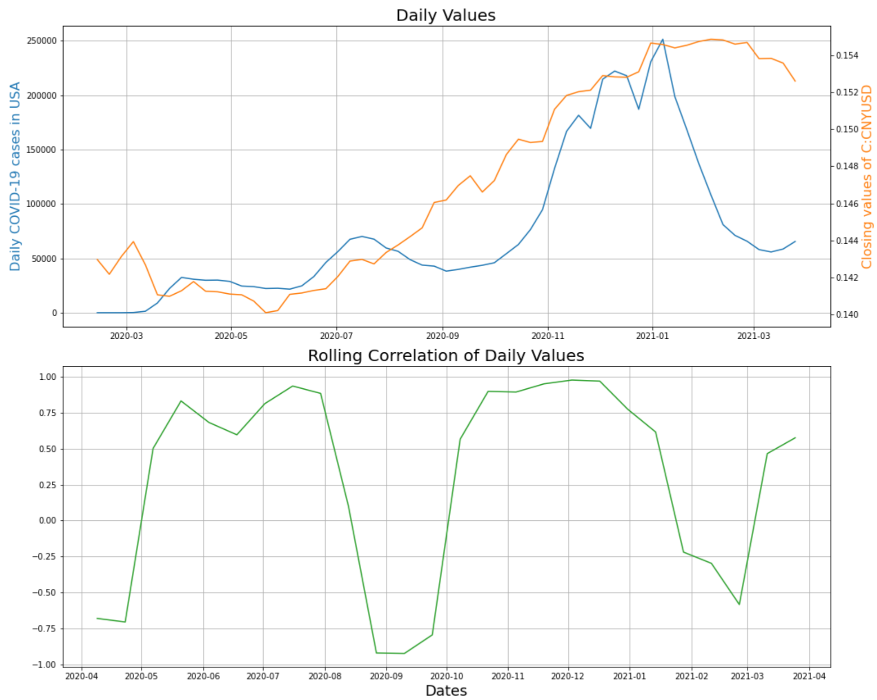

Figure 17. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair CNYUSD.

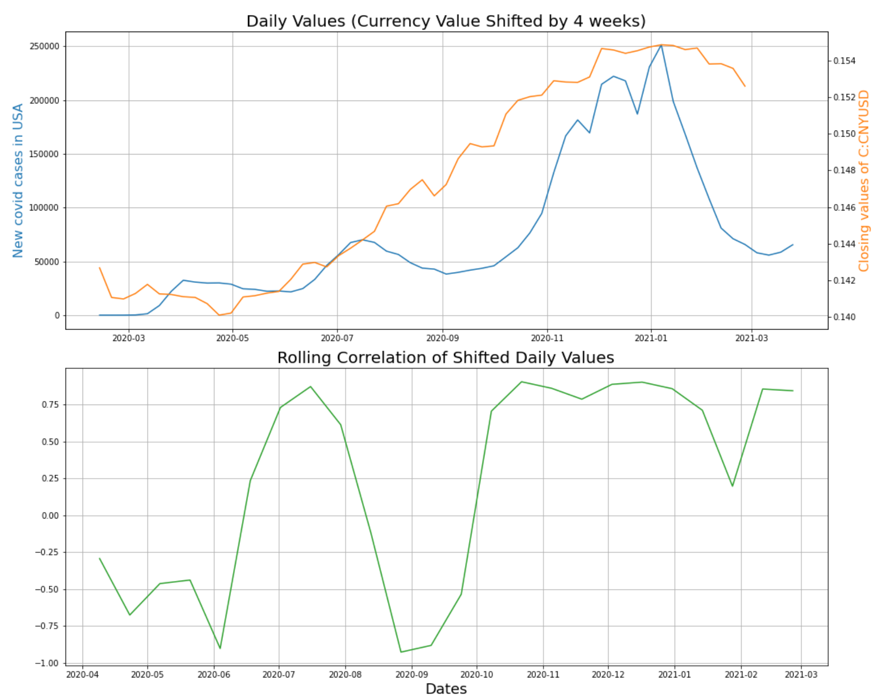

Figure 18. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair CNYUSD shifted by a month to the left.

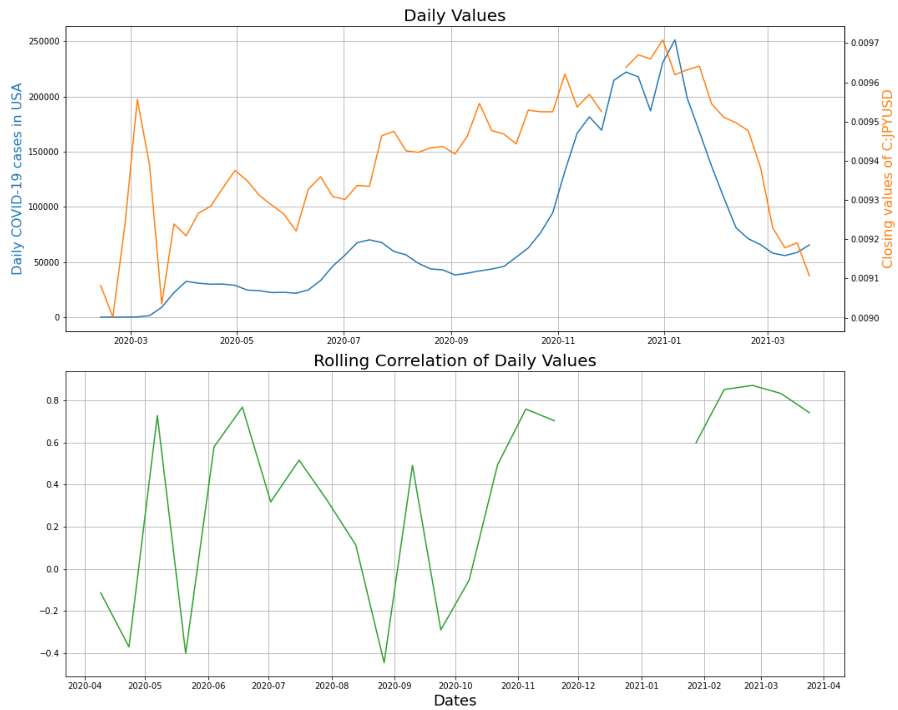

Figure 19. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair JPYUSD.

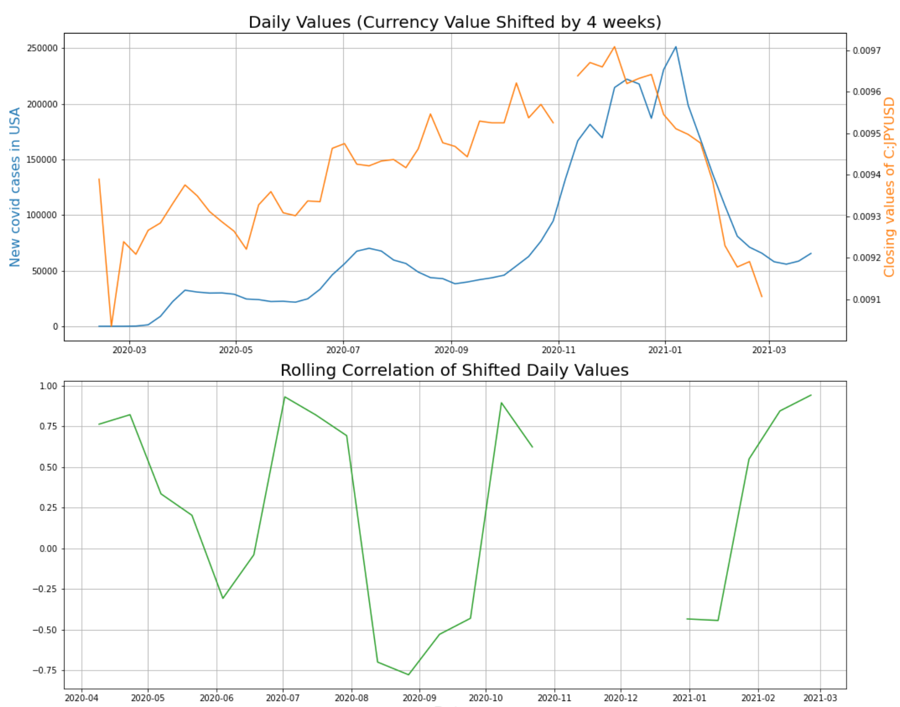

Figure 20. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of the foreign exchange currency pair JPYUSD shifted by a month to the left.

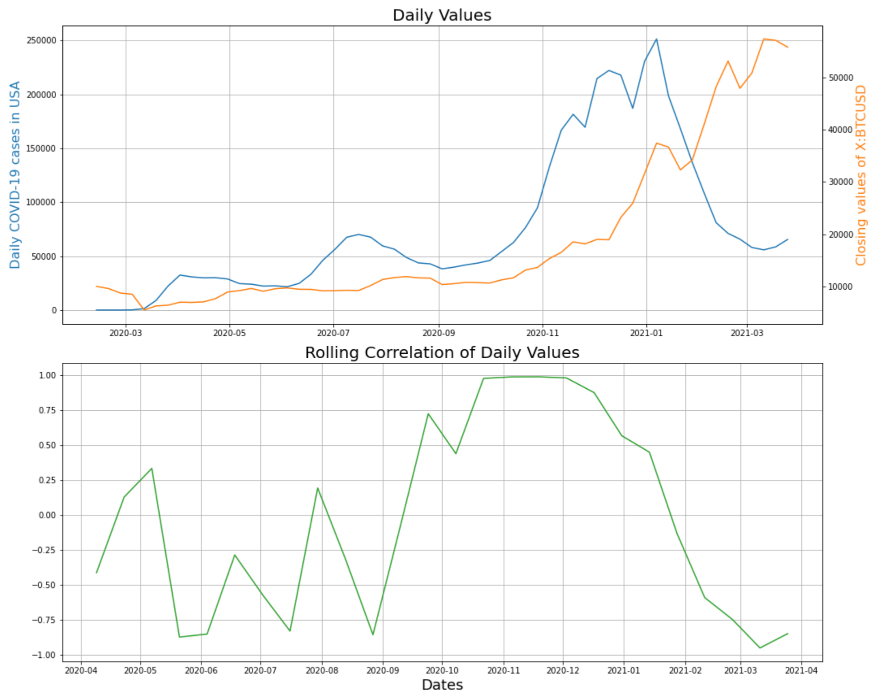

Figure 21. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of bitcoin.

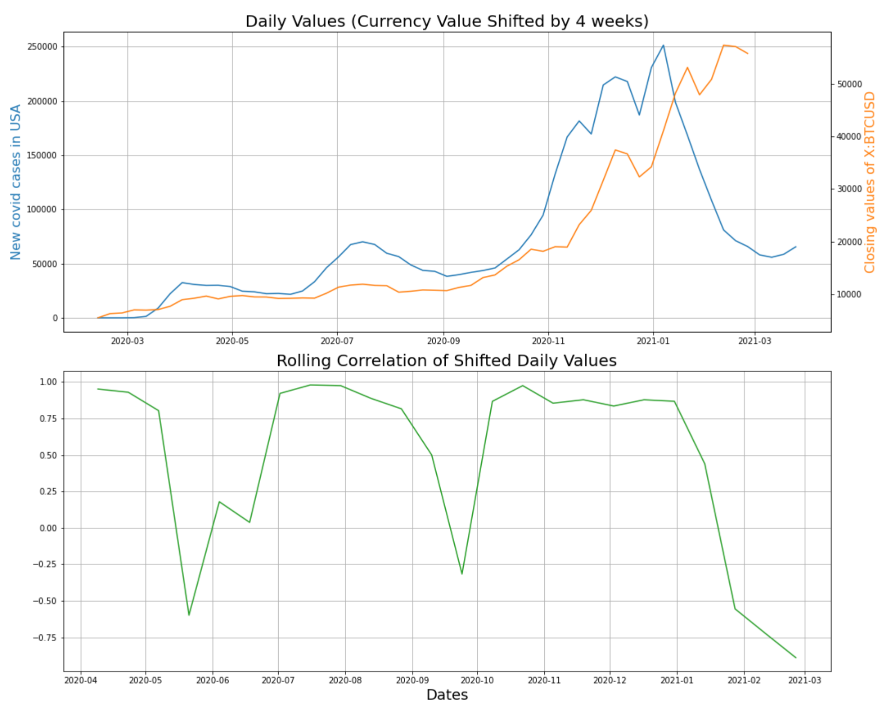

Figure 22. The rolling correlation between COVID-19 daily new cases in the USA and closing price values of bitcoin shifted by a month to the left.

Query 6: Correlation of cryptocurrency and foreign exchange pair measurements

Finally, the correlation between cryptocurrency and foreign exchange currency pairs was examined, by looking at the weekly closing price, trading volume, and number of transactions of each currency. The weekly plots were obtained by the exponential moving average function, where the moving window was set to 8 data values, signifying a 8week moving window (Figures 23-26). After observing various pairs of measurements of cryptocurrencies and foreign exchange pairs and calculating the correlation of the weekly plots as a whole, bitcoin's weekly number of transactions and the weekly closing price of foreign exchange pair EURUSD had the highest correlation with the value 0.546 (Figure 27). The rolling correlation of these two weekly plots were calculated with a 8week window (Figure 28) and was concluded that there is no direct /consistent correlation between cryptocurrency and foreign exchange currency pairs measurement.

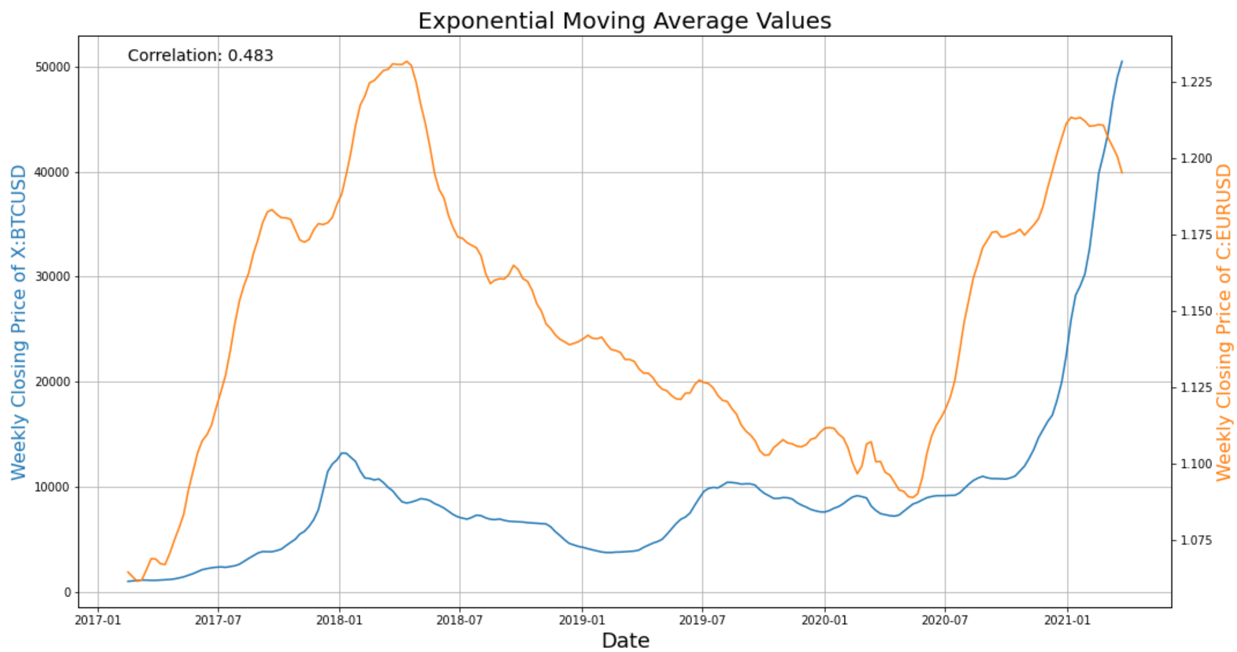

Figure 23. Plot of weekly values of bitcoin and foreign exchange currency pair EURUSD closing price using exponential moving average.

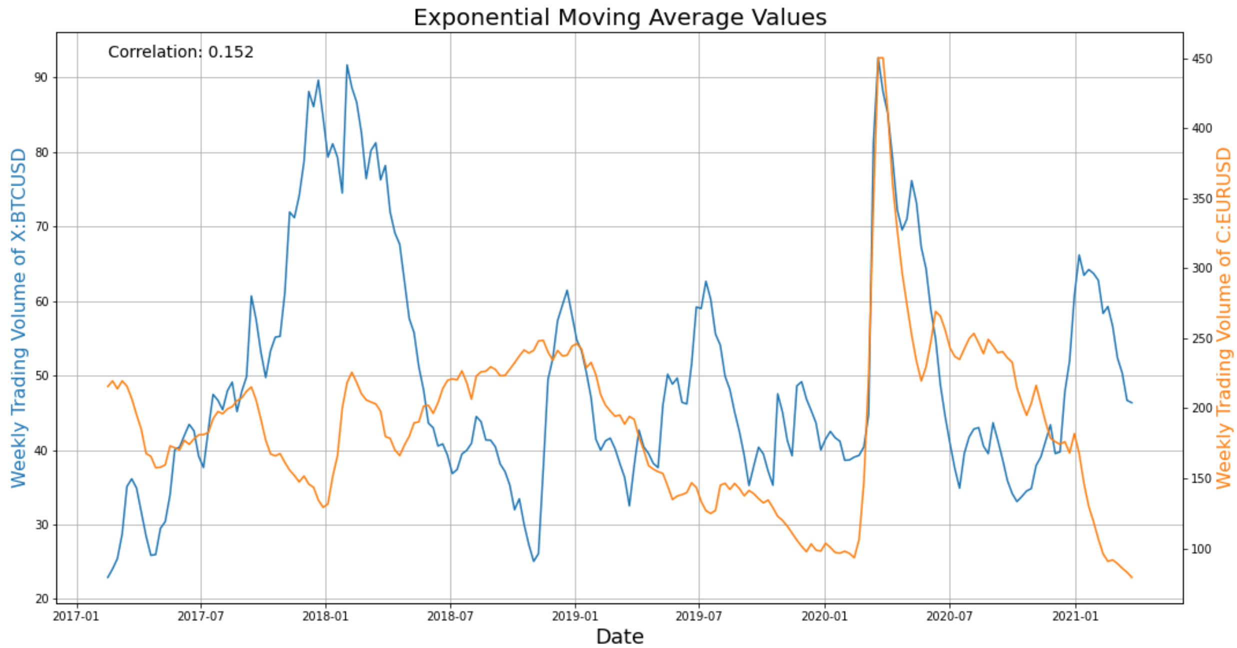

Figure 24. Plot of weekly values of bitcoin and foreign exchange currency pair EURUSD trading volume using exponential moving average.

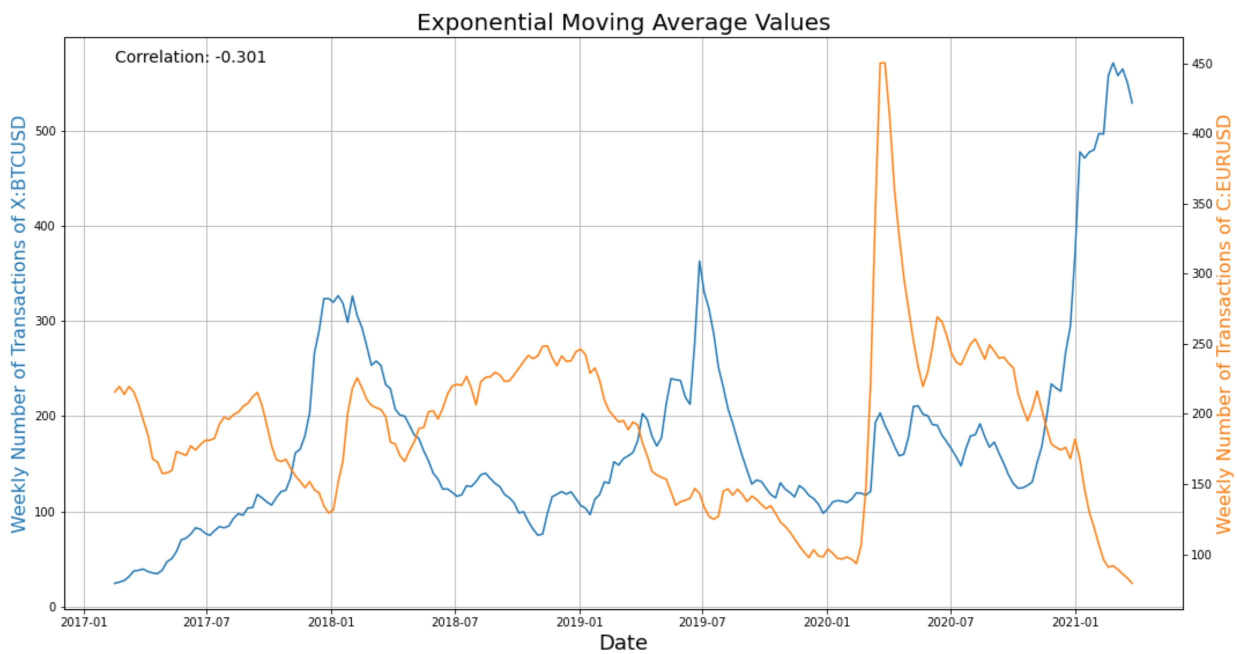

Figure 25. Plot of weekly values of bitcoin and foreign exchange currency pair EURUSD number of transactions using exponential moving average.

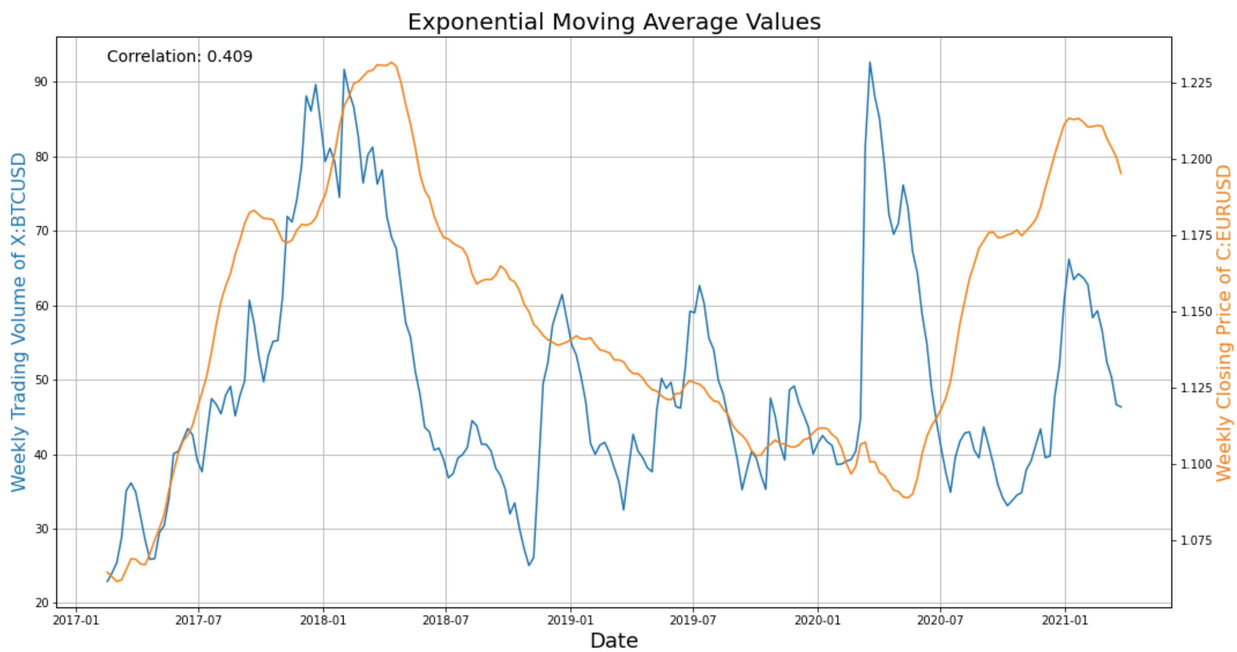

Figure 26. Plot of weekly values of bitcoin trading volume and foreign exchange currency pair EURUSD closing price using exponential moving average.

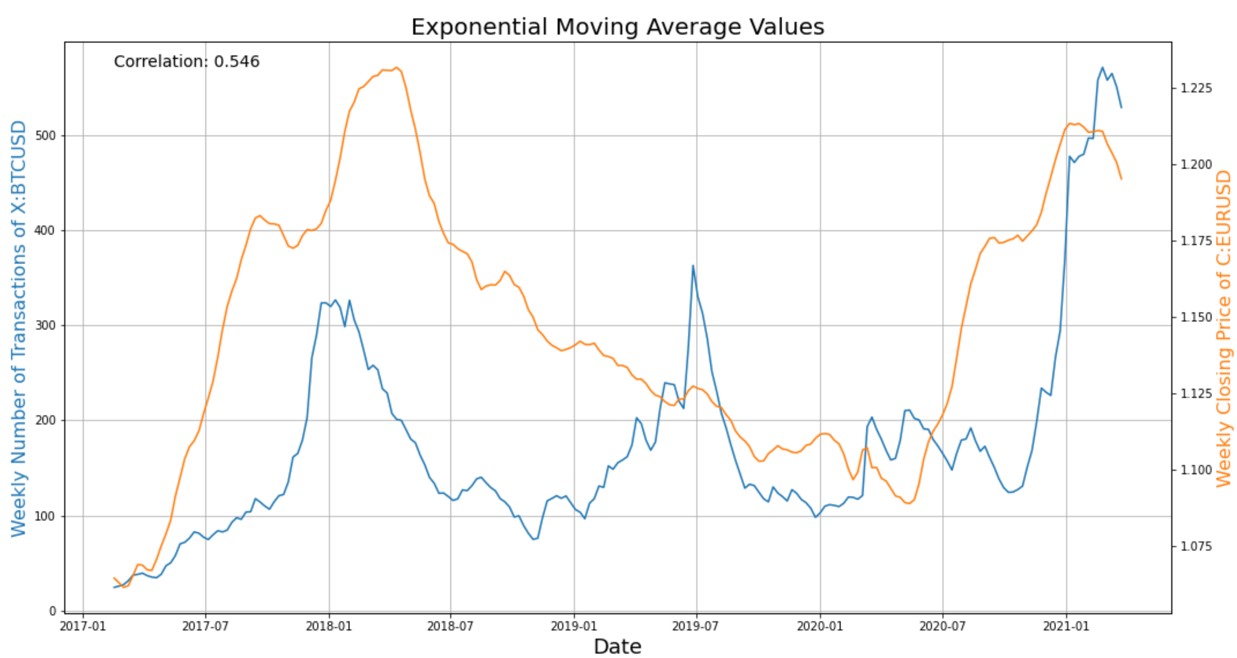

Figure 27. Plot of weekly values of bitcoin number of transaction and foreign exchange currency pair EURUSD closing price using exponential moving average.

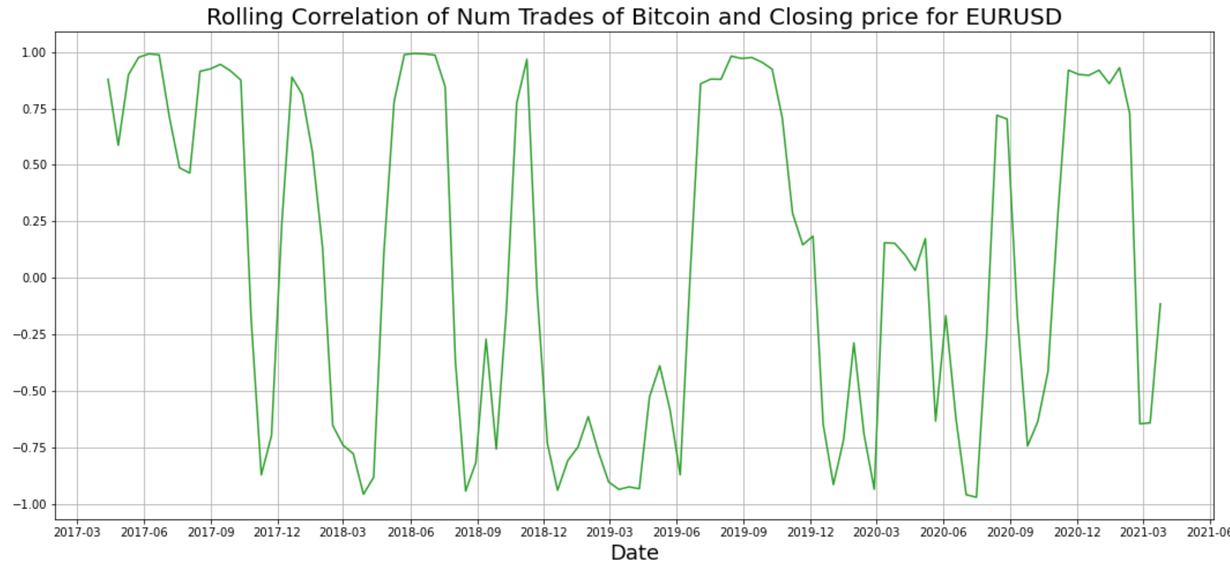

Figure 28. The rolling correlation between weekly values of bitcoin number of transaction and foreign exchange currency pair EURUSD closing price

Discussion

Discovered Problems

Polygon.io stood out as an obvious choice due to its thorough documentation. However, the project required more complicated requests than what Polygon.io offered by default. There is a standard endpoint in the official documentation that provides "aggregate bars for a currency over a given date range in custom time window sizes." This endpoint is fully functional, but it is limited to under 50,000 data points per request. A month of data with a minute resolution is around 45,000 data points. As a result, it was necessary to chain these requests together. So, first, a python script had to be written to make a request to the polygon.io endpoint, and then another script had to be written to call this script repeatedly, saving the results in the same file. Since the project required 37 currencies total, the project required another script. To avoid getting kicked off of the Polygon.io servers, the script required sleep statements, which led to a lengthy data pull process.

While InfluxDB was smooth for loading our COVID-19 dataset, there were some issues with loading the data from Polygon.io. The issue that occured was that the unix timestamps would be registered as null in the InfluxDB database, which by default is the date '1970-01-01,' so there were millions of points on a single date. This prevented us from doing any data analysis. As a result, a conversion method was used to put the unix timestamps in the proper format that InfluxDB could understand. Unfortunately, using this method led to a drastic increase in time to load the data. In addition, there was an issue with typing when loading the database. Some values were floats, and some were integers. This led to many dropped data points, but was resolved when all numerical fields were converted to floats. This process taught us that preparing data takes much longer than querying data.

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