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Unravelling Cryptocurrency and Stock Market Dynamics: Predictive Models and Macroeconomic Implications

MSc Research Project
FinTech

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MSc Project Submission Sheet

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Programme: ……… MSc FinTech ……………………………… **Year:** … 2022/23 ..

Module: ……… MSc Research Project ………………………………………………….………

Supervisor: ……… Brian Byrne ………………………………………………………….………

Submission Due Date: ……… 14/08/2023 ..………………………………………………………….………

Project Title: ……… Unravelling Cryptocurrency and Stock Market Dynamics: Predictive Models and Macroeconomic Implications ………

Word Count: …… 6356 …… **Page Count** ………… 17 ……………….……..

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Unravelling Cryptocurrency and Stock Market Dynamics: Predictive Models and Macroeconomic Implications

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Abstract

This study examines the complex relationships between cryptocurrencies and stock markets, including volatility dynamics, price prediction, and the influence of macroeconomic factors. Using a variety of models, including ARIMA, VAR, and LSTM, and leveraging feature importance analysis with Random Forest regression, our research reveals significant correlations between cryptocurrency and stock markets, which are accentuated during times of economic uncertainty. The LSTM model forecasts cryptocurrency prices with the highest accuracy among all predictive models. The findings demonstrate the importance of stock market performance and interest rates in determining the price trends of cryptocurrencies. Our research has implications for both academics and investors, promoting informed investment decisions. Future research should expand sample sizes and investigate a broader range of macroeconomic factors, thereby enhancing our understanding of this intricate financial interaction.

Keywords: Cryptocurrency, Stock Markets, Price Predictions, Macroeconomic Indicators, Machine Learning Models

1 Introduction

As a new type of asset, cryptocurrency has received a great deal of interest in recent years. The decentralised nature of cryptocurrencies and their potential to revolutionise the financial industry have sparked increased interest among investors, speculators, and researchers. Due to the inexpensive, anonymity, and online accessibility of cryptocurrencies, they are being used to implement a new economic system. The fundamental of cryptocurrency relies on blockchain technology that maintains a record of all transactions conducted in any cryptocurrency using a network of interconnected computers. Essentially, it is a potent technology with the capacity to maintain permanent data of commercial transactions, and asset transfers including financial records, digital contracts, and intellectual property rights. Moreover, cryptocurrencies are deemed immune to monetary interventions and fiscal policies as they are not subject to centralised authority, hence their highly volatile nature (Choo, 2015).

The most popular cryptocurrency, Bitcoin is restricted to 21 million units, which is also often termed "deflationary currency". Bitcoin's rise to prominence on the international financial scene has been widely documented in the media ever since its debut in 2008, which coincided with the global financial crisis and a widespread loss of faith in the financial system (Sebastião and Godinho, 2021). Bitcoin began as a retail investment asset, and has since become the fundamental principle against all other digital currencies, such as Ethereum, Ripple, Tether, etc. Bitcoin had been profitable, but the boom of trading accelerated during the COVID-19 outbreak, with an increasing number of people beginning trading Bitcoin its value peaked in 2021 at $63,729.50. The market capitalisation of cryptocurrencies exceeded USD 2.8 trillion in November 2021[1]. Cryptocurrencies could be advantageous compared to fiat currencies for having a fixed supply that prevents overprinting manipulation. However, crypto markets have liquidity difficulties which prevent market participants from closing their positions at the optimal price. The subsequent reluctance of investors to reintroduce the coins to the market may result in a market-wide influx that affects the market's volatility and efficiency. The market for cryptocurrencies has evolved from digital curiosities to trillion-dollar technologies with the potential to disrupt the global financial system.

The dramatic emergence of cryptocurrencies has presented investors and regulators with new challenges. In 2022, as interest rates were rising, Bitcoin prices dropped as investors dumped the hazardous asset due to the market's inherent volatility. Moreover, a variety of macroeconomic variables, such as inflation, GDP, and commodity prices could influence the volatility of cryptocurrencies and stock markets (Chun, Cho and Ryu, 2023). It is vital to comprehend the impact of macroeconomic drivers on the volatility of cryptocurrencies and stock markets as it has been demonstrated that both are heavily associated (Jeris *et al.*, 2022). This research investigates the relationship between cryptocurrencies and the stock market, makes price predictions for cryptocurrencies, and identifies the macroeconomic variables that influence cryptocurrency prices. The primary focus is to resolve financial and economic concerns through simplified discussion.

To accomplish the research goals, numerous statistical and machine learning techniques including cointegration tests, Autoregressive Integrated Moving Average (ARIMA), Vector Auto-Regressive (VAR), Long-Short Term Memory (LSTM), and Random Forest (RF) are employed. This study utilises historical data on the S&P Cryptocurrency Broad Digital Market Index, the S&P500 Index, Consumer Price Index (CPI), exchange rates, short-term interest rates, and the Economic Policy Uncertainty (EPU) Index as a possible empirical substantiation of the Efficient Market Hypothesis (EMH) by exploring the correlation between cryptocurrency prices with these variables using machine learning framework.

1.1 Research Question

To what extent is the relationship between stock prices and cryptocurrencies, and how do macroeconomic factors affect the prices of cryptocurrencies?

1.2 Research Objectives

The objectives of the research are:

- To analyse the relationship between the stock market and digital assets.
- To predict cryptocurrency prices based on historical data.
- To identify the macroeconomic variables that impact the volatility of cryptocurrencies.
- To evaluate the performance of the machine learning models and compare them with traditional econometric models.

[1] CoinMarketCap. (2023). Global Cryptocurrency Charts. https://coinmarketcap.com/charts/

The structure of the report is as follows: Section 2 provides a literature review on the related topics to date. Section 3 discusses the methodology, while Section 4 describes the design specification and models utilised for prediction. Section 5 showcases implementations taken to conduct the research, Section 6 discusses the analysis outcomes, followed by evaluations and discussions with concluding remarks in Section 7.

2 Related Work

This section discusses cryptocurrency's volatility, stability, and economic influence. In both developed and emerging economies, the extent of its relationship to the stock market is thoroughly examined. Numerous statistical and machine learning studies have examined the predictability of cryptocurrency prices, while some have examined the impact of macroeconomic factors on cryptocurrency prices. These studies were reviewed to determine which macroeconomic drivers to include in this research. The purpose is to highlight the primary research objectives and contributions of these studies to critically compare their findings. The literature review will be divided into three sections, with each section focusing on a distinct aspect of the literature.

2.1 Volatility Between Cryptocurrencies and Stock Markets

Investors are influenced by financial turmoil. Academics and investors are studying the stock market-cryptocurrency link. During times of turmoil, investors are more likely to redistribute their holdings to assets regarded as safe havens. However, research suggests cryptocurrency may not be a secure investment. Coincident with the COVID-19 outbreak, the correlation between Bitcoin and S&P500 volatility increased, it indicates that the co-movement between Bitcoin and the S&P500 is moment-dependent and frequency-dependent (Bouri, Kristoufek and Azoury, 2022). Nguyen (2022) stated that Bitcoin's volatility was affected by the financial market impetus during the COVID-19 turmoil. The author concluded that cryptocurrency and stock markets are more intertwined during uncertain times. Moreover, the COVID-19 turbulence has significantly impacted both long-term memory and the volatility of cryptocurrencies and global stock markets (Lahmiri and Bekiros, 2021). A systematic evaluation of the relationship between cryptocurrency and the equity market was investigated by (Jeris *et al.*, 2022), with results indicating a significant relationship between cryptocurrency and the stock market. Similarly, (Wang, Xue and Liu, 2016) discovered that the long-term relationship between the stock prices and Bitcoin price is stable, but the short-term relationship is dynamic. A change in the stock price index has a significant impact on Bitcoin prices, as investors tend to enter and exit the market in response to fluctuations. Corbet, Katsiampa and Lau (2020) used Granger-causality tests to demonstrate evidence that Bitcoin reflects the same trend as financial markets, being a safe haven for oil but not the S&P500 or gold. This is consistent with the findings of Ji, Zhang and Zhao (2020) who discovered that cryptocurrencies have a substantial influence on the stock market, with positive spillover effects during periods of extreme volatility.

On the other hand, Bouri and Azzi (2016) discover no evidence of an asymmetric return-volatility relationship in the Bitcoin market which supports Bitcoin's safe-haven quality. Furthermore, Jeribi and Ghorbel (2022) and (Lahiani, Jeribi and Jlassi, 2021) independently analysed the correlation between the top five leading cryptocurrencies (Bitcoin, Ethereum, Monero, Dash, and Ripple) with the BRICS market and advanced economy, but neither found a significant correlation between cryptocurrencies and the BRICS market compared to an advanced economy. Their findings suggest Bitcoin to be a new gold due to its hedging properties. It was also unveiled that there is weak and frequently time-varying integration between cryptocurrencies and equity markets in the event of shocks. Litecoin has a negative correlation with the Japanese stock market index, indicating that Litecoin may function as a stable, secure reserve for the Japanese stock market index in the short run when the global economy is in decline (Umar *et al.*, 2020). This echoes the research conducted by (Tiwari, Raheem and Kang, 2019) where the time-varying asymmetric connection between cryptocurrencies and the US stock market is examined and their findings revealed that Litecoin is the most effective financial hedge against the volatility of the US stock market. Despite having the greatest market share, Bitcoin is not representative of the entire cryptocurrency market in most of the literature. This is another research niche that this paper aims to address. The hypothesis for this sub-section is developed as below:

H_0: There is a correlation between cryptocurrency and the stock market due to volatility spillovers.

2.2 Cryptocurrency Prices Prediction

Early Bitcoin studies debated whether it was a currency or a speculative asset, with most writers favouring the latter due to its extreme volatility, exaggerated short-term gains, and bubble-like price behaviour. For instance, Cheah and Fry (2015) concluded that Bitcoin is a speculative bubble with negative inherent value. Financial economists investigate stock market EMH using the price-volume paradigm. Thus, (Sahoo and Sethi, 2022) examine bitcoin market forecasting using a price-volume paradigm. They found that overall volume cannot predict cryptocurrency returns, validating the EMH. It is now widely acknowledged that cryptocurrency returns and volatility are especially sensitive to shocks and news, such as the hacking and bankruptcies of numerous cryptocurrency exchanges, the repeated announcements by multiple jurisdictions to ban or regulate cryptocurrency markets, and several major international banks adopting Ripple. Scholars have long debated cryptocurrency asset price fundamentals. (Li and Wang, 2017) argued that "public recognition" is the primary factor influencing the price of Bitcoin. This hypothesis was tested for various cryptocurrencies. (Phillips and Gorse, 2017) studied if the market regime affects the relationships between online and social media elements and the prices of cryptocurrencies. They noticed that medium-term positive correlations increase substantially during bubble-like policies, while short-term relationships appear to be caused by specific market events, such as hacks or security breaches.

Researchers and investors are equally interested in the predictability of cryptocurrency prices. A study by (Sebastião and Godinho, 2021) analysed the predictability of cryptocurrencies and the profitability of trading strategies based on Linear Models, Random Forests, and Support Vector Machines (SVMs) but there is no discernible pattern to determine which model is superior. Numerous machine learning models were built in time-series analysis to predict the future, each with their strengths and weaknesses (Laboissiere, Fernandes and Lage, 2015; Chen, Li and Sun, 2020; Kumar Singh, Pal Sharma and Kumar,

2022). (Iqbal *et al.*, 2021) sampled time-series data with varying market information frequencies. For the prediction, they used three machine-learning techniques: ARIMA, FBProphet, and XGBoost. ARIMA is the best algorithm for forecasting changes in the market price of Bitcoin. Another related work by (Dimitriadou and Gregoriou, 2023) developed a model capable of predicting Bitcoin price fluctuations and to determine whether it follows the EMH or a random walk using logistic regressions, SVMs, and Random Forest to demonstrate the predictability of price movements. Their results showed that a traditional logit model performed the best (accuracy of 66%) in predicting Bitcoin price movements. Additionally, it has been proven that LSTM is an effective method for predicting Bitcoin prices, and the model attained a high degree of accuracy. For instance, (Ferdiansyah *et al.*, 2019) created a model using LSTM for predicting Bitcoin stock market prices while (Kim and Won, 2018) proposed a hybrid model that combines LSTM with a variety of GARCH-type models to predict stock price volatility. (Zhang *et al.*, 2022) proposed a novel Bitcoin and gold prices prediction method using an LSTM-P neural network model with high accuracy in anticipating future prices.
H_0: Machine learning algorithms will outperform traditional econometric models in price prediction.

2.3 The Impact of Macroeconomic Factors on Cryptocurrencies and Stock Markets

Cryptocurrencies are generally known to respond to certain market announcements (Hashemi Joo, Nishikawa and Dandapani, 2020). Cryptocurrency prices reflect real-world data nearly instantly, making the market efficient. A branch of research examines how macroeconomic news affects bitcoin prices (Goodell *et al.*, 2023). Cryptocurrency and stock market volatility have been linked to macroeconomic variables such as inflation, exchange rates, and interest rates. However, research on the effect of these factors on the interplay of the two markets is scarce. According to a study by (Keswani and Wadhwa, 2018), they concluded there is a strong long-term relationship between government policies, disposable income, inflation, exchange rates, and interest rates on the Bombay Stock Exchange using Vector Error Correction Model (VECM). On the other hand, Bitcoin is not regarded as the perfect hedging device against stock markets, inflation, and federal funds rates but could be a good oil price hedge (Srinivasan and Kumar, 2022). When a high rate of inflation can cause a decline in the cryptocurrency market, this indicates that inflation may have a negative effect on the prices of cryptocurrencies.

Several studies on the relationship between exchange rates and cryptocurrencies have been conducted. Most researchers wish to determine whether there is a correlation between the exchange rate and the price of cryptocurrencies. Using GARCH-type models, (Samah, Wajdi and Regaieg, 2018) demonstrated a significant correlation between Bitcoin, the exchange rate, and gold prices. Using Autoregressive Distributed Lag (ARDL) test model, (Angela and Sun, 2020) concluded that the EUR/USD affects Ethereum prices only in the short term, whereas gold prices have no influence on Ethereum prices. Conversely, (Dimitriadou and Gregoriou, 2023) suggested the returns of Bitcoin to be unrelated to the returns from different cryptocurrencies or to macroeconomic variables. They proposed that Bitcoin is an asset distinct from economic policy and other digital currencies, where it could serve as a hedge against inflation and interest rate policies. Likewise, (Kusumastuty *et al.*, 2019) revealed the impact of monetary variables on cryptocurrency prices using the VAR model and concluded that there is no significant impact of monetary variables on cryptocurrency prices in the initial phase. However, results from subsequent phases of the study suggested a significant relationship. The Economic Policy Uncertainty (EPU) index[2] is another commonly studied macroeconomic element that has been shown to have a negative effect on global macroeconomic performance and to increase the ability to anticipate future real economic activity (Baker, Bloom and Davis, 2016; Caldara *et al.*, 2016). (Hung, Huynh and Nasir, 2023) revealed a negative relationship between Bitcoin prices and the key selected uncertainty indices[3], indicating that greater uncertainties lead to less Bitcoin price volatility across time and frequency domains. Bitcoin prices and CPI, EPU, and the money supply interact dynamically. Bitcoin's hedging asset role is supported by CPI's short-term price boost (Wang, Sarker and Bouri, 2022). Bagging and Random Forests predicted Bitcoin and gold prices (Basher and Sadorsky, 2022), they found that long-term interest rates and the oil volatility index (OVX) are the most important macroeconomic factors, while the inflation rate has no effect on predicting Bitcoin's price.

H_0: CPI, exchange rates, interest rates, and EPU have a negative impact on cryptocurrency prices.

Overall, the use of machine learning algorithms to analyse the relationship between cryptocurrency and equity markets is effective at predicting trends and identifying significant factors influencing the two markets.

3 Research Methodology

To achieve the research objectives, the Knowledge Discovery in Database (KDD) approach is used to extract knowledge from the data. This involves data selection, preprocessing, transformation, data mining, pattern evaluation, and knowledge representation.

3.1 Data Collection and Selected Variables

This research utilises historical data on the S&P Cryptocurrency Broad Digital Market Index[4], the S&P500 Index, exchange rates of major traded currencies (GBP/JPY, EUR/CAD, AUD/CNY), short-term interest rates, CPI, and EPU index. These variables were chosen based on their applicability to the research objectives and their prospective impact on cryptocurrency prices.

- Cryptocurrency Index and Stock Index:

The S&P Cryptocurrency BDM Index comprises of 240 coins, which provides a broad performance view of the cryptocurrency market. The index tracks digital assets that satisfy minimum liquidity and reflects a vast universe of investable assets weighted on market

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[2] Economic Policy Uncertainty Index. https://www.policyuncertainty.com/index.html
[3] Global Economic Policy Uncertainty, Twitter-based Economic Uncertainty, Equity Market Volatility, The Cryptocurrency Policy Uncertainty Index, Geopolitical risk index, and The Cryptocurrency Price Uncertainty Index.
[4] S&P Cryptocurrency Broad Digital Market Index. https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-broad-digital-market-index/#overview

capitalisation. The S&P500 Index is widely acknowledged as a benchmark for the performance of the US equity market and functions as an indicator of market trends and investor sentiment.

- Exchange rates:

The selection of key traded currency exchange rates, such as GBP/JPY, EUR/CAD, and AUD/CNY, is motivated by the potential impact of currency fluctuations on the prices of cryptocurrencies. These currency exchange rates represent significant currency pairings that reflect global economic dynamics and currency market fluctuations.

- Short-term interest rates:

  Changes in interest rates can influence investment decisions, risk tolerance, and capital flows, thereby influencing the price of cryptocurrencies.

- Inflation:

The CPI is an essential macroeconomic indicator that reflects changes in the general price level of products and services. Inflation can affect purchasing power, investment decisions, and market expectations, making it pertinent for analysing the price dynamics of cryptocurrencies.

- Economic Policy Uncertainty (EPU) index:

The EPU index is regarded as a measure of the uncertainty surrounding economic policy decisions. It acts as a proxy for market sentiment, risk aversion, and the overall economic climate, thereby influencing the price of cryptocurrencies.

The data is collected from reliable sources such as official sites, Yahoo Finance, and FRED. Since different sources are involved, the data is downloaded on Python using the yfinance package and then merged into a single CSV file for analysis. The sampling period for the analysis extends from 01/03/2017 to 28/04/2023, inclusive) with a daily frequency on trading days, comprising a substantial window of time to capture various market conditions and potential changes in the relationship between variables.

3.2 Data Preprocessing

Prior to model development, an exploratory data analysis (EDA) is conducted to understand the characteristics and distributions of the collected data. Descriptive statistics, visualisations, and correlation analysis are performed to identify potential relationships and patterns among variables. The returns of closing prices for both cryptocurrency and the stock market are derived, and the raw data is pre-processed to ensure stationarity. This technique includes generating the returns of the variables and removing the trend and seasonality from the series. The next section will discuss the econometric models and machine learning techniques implemented to attain the research objectives.

4 Design Specification

In this section, the implementation details and methodologies underlying the development and execution of the proposed solutions are described, with an emphasis on the steps taken to meet each research objective.

4.1 Cointegration Analysis

Financial theory should propose the existence of a long-term relationship between two or more variables. Cointegration tests are utilised to investigate the connection between cryptocurrencies and the stock market. The Johansen cointegration test is used to determine the existence and intensity of a long-term relationship between the S&P Cryptocurrency BDM Index and the S&P500 Index. Additionally, the Engle-Granger and VECM tests are used to confirm the results of the Johansen test.

- Johansen Cointegration test

The Johansen test is a popular cointegration test that determines the long-run correlations between variables. It identifies the presence and extent of cointegration between cryptocurrency markets and stock markets.

- Engle-Granger test

The cointegration of two time series can be investigated using the bivariate Engle-Granger test. The test relies on the differences between the residuals of one time series and the other.

- Vector Error Correction Model (VECM)

The VECM can be utilised in modelling the dynamics of cointegrated time series. It enables the analysis of the short-term dynamics of variables while considering their long-run equilibrium relationship (Keilbar and Zhang, 2021).

Table 1: Hypotheses of the different cointegration tests

Test	Null Hypothesis	Alternative Hypothesis
Johansen test	There are no cointegration relations between the time series.	There is at least one cointegration relation between the time series.
Engle-Granger test	The residuals from the regression of one time series on the other time series are not stationary.	The residuals from the regression of one time series on the other time series are stationary.
VECM	The error correction term is not significant.	The error correction term is significant.

4.2 Cryptocurrency Price Prediction

Before proceeding to price prediction, GARCH is used to estimate the volatility of cryptocurrency returns.

- Generalised Autoregressive Conditional Heteroskedasticity (GARCH)

A GARCH (p, q) model includes conditional variance extended from the ARCH (q) model. The GARCH model enables the conditional variance to depend on own lags, which means the conditional variance equation for the simplest case is now:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The above is a GARCH (1,1) model and it is known as the conditional variance because it is a one-period-ahead estimate of the variance based on any relevant historical information (Brooks, 2019). GARCH models presume the error variance follows an autoregressive moving average process, they are particularly helpful when the objective of the study is to analyse and predict volatility.

The statistical predictive models are ARIMA and VAR while LSTM is the machine learning algorithm:

- Auto-Regressive Integrated Moving Average (ARIMA)

The objective of ARIMA models is to explain the autocorrelations in the dataset. ARIMA stands for Auto-Regressive Integrated Moving Average (where "integration" is the opposite of "difference"). The model can be expressed as:

$$y'_t = c + \emptyset_1 y'_{t-1} + \cdots + \emptyset_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots\; (2)$$

where y'_t is the series that has been differentiated. The right-hand "predictors" include both lagged y'_t values and lagged error values. This is known as an ARIMA(p,d,q) model, where the parameters are: the order of autoregression (p), the degree of differencing (d, and the order of the moving average (q) (Hyndman and Athanasopoulos, 2021). The ARIMA can be used to forecast time series data. In this case, cryptocurrency prices.

- Vector Auto-Regressive (VAR)

A VAR is a systems regression model (i.e., there are multiple dependent variables) that can be thought of as a hybrid of univariate time-series models and simultaneous equations. VARs enable the significance of a variable to depend on in addition to its own lags or combinations of white noise terms; therefore, VARs are more flexible than univariate AR models. Therefore, VAR models can offer a very complex structure, indicating that they may be able to capture more data characteristics. It is used to forecast the prices of cryptocurrency constituents and indices. VAR enables the analysis of the short-term dynamics of variables while considering their long-run equilibrium relationship.

- Long Short-Term Memory (LSTM)

LSTM is a deep learning model that can be used in price forecasting. It is a form of recurrent neural network (RNN) that can process complex time-series data with long-term dependencies. A hybrid LSTM-GARCH model can be used to predict the volatility of cryptocurrency portfolios. In terms of anticipating the volatility of cryptocurrency portfolios, the LSTM-GARCH hybrid model excelled over other models, as demonstrated by (Kim and Won, 2018). LSTMs work by using a gating mechanism to control the flow of information through the network. The gating mechanism consists of three gates: the input gate, the hidden gate, and the output gate. Future cryptocurrency values can be predicted using LSTM.

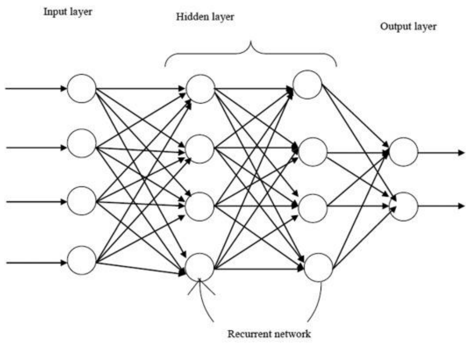


Figure 1: A neural network with inputs and hidden layers before generating its outputs.

4.3 Features Importance Analysis

Random Forest (RF) is a decision-tree-based ensemble machine learning method applicable to both regression and classification problems. The RF algorithm is used to identify the significant variables that influence the prices of cryptocurrencies. The RF model is trained using the selected features, and the variables' importance scores are computed. The feature importance analysis reveals the relative contributions of each macroeconomic indicator in predicting the prices of cryptocurrencies.

4.4 Evaluation Metrics

The evaluation metrics used are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). These error metrics reflect the average differences between the predicted and actual values, hence smaller values indicate the model's higher accuracy. Meanwhile, a higher R^2 value between 0.7 and 1 signifies a strong correlation between the observed and predicted values, implying a better fit between the model and the data. This will be discussed thoroughly in Section 6.

5 Implementation

The analyses are conducted using Python with the processing environment set by Google Colab. The steps involved in the implementation include modelling, analysis, interpretation, and evaluation.

I. **Step one:** The dataset was collected from different sources such as Yahoo Finance, FRED, and official sites. Necessary rescaling was done to convert monthly data to daily frequency. It consists of 1540 observations after taking returns on each variable.
II. **Step two:** The packages and libraries installed in Python are (yfinance), (pandas-datareader), (arch), (pmdarima), (sklearn), (statsmodels), (keras), (matplotlib), and (seaborn) to analyse and evaluate the data.
III. **Step three:** This phase includes feature engineering, which entailed examining datasets for missing values, summaries, and descriptive statistics. Table 2 shows the descriptive statistics and Figure 4 shows the correlation matrix of all variables.
IV. **Step four:** Necessary transformations such as generating the returns of the variables and applying log when examining both indices were done. Diagnostic checks such as

detection for multicollinearity, autocorrelation, heteroscedasticity, and normality were conducted.

V. **Step five:** Unit root tests such as the ADF tests were performed, and the dataset has achieved stationarity at first-level difference.

VI. **Step six:** Cointegration tests were conducted to explore the short and long-term dynamics of the S&P Crypto BDM Index and the S&P500 Index.

VII. **Step seven:** ARCH tests were carried out before modelling GARCH (1,1) to examine the explosive volatility in cryptocurrency prices. This step is crucial as it depicts the prediction of cryptocurrency prices.

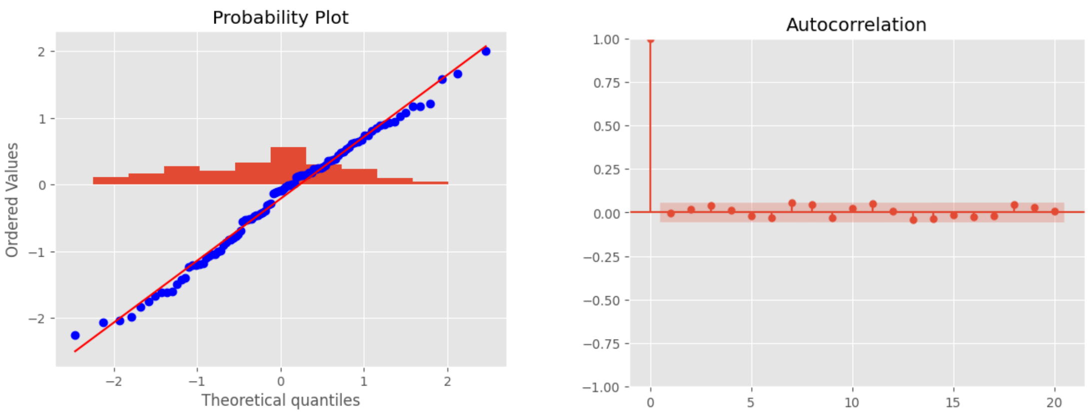
VIII. **Step eight:** Econometric models such as ARIMA and VAR were utilised to forecast the prices of cryptocurrencies and to be compared to the accuracy of machine learning models such as the LSTM.

IX. **Step nine:** Feature importance analysis conducted using Random forests to identify the significant macroeconomic indicators that affect cryptocurrency prices.

5.1 Explanatory Data Analysis (EDA)

Table 2: Descriptive statistics of the returns on the variables.

Statistics	Crypto	SP500	GBPJPY	EURCAD	AUDCNY	Interest_Rates	CPI	EPU
count	1540	1540	1540	1540	1540	1540	1540	1540
mean	0.003177	0.00041	0.000136	0.000052	-0.000065	0.006838	0.000286	0.002977
std	0.048398	0.012742	0.006477	0.004628	0.006607	0.216573	0.015295	0.003429
min	-0.241241	-0.119841	-0.038425	-0.024274	-0.029262	-5.000000	-0.105194	-0.006687
max	0.206094	0.093828	0.031016	0.031705	0.036026	3.000000	0.093396	0.013736



Figures 2 & 3: Probability plot and ACF plot of the returns dataset.

Based on the Shapiro-Wilk test and Jarque-Bera test conducted, it is safe to say that the data is approximately normally distributed. The autocorrelation function (ACF) shows a significant peak at lag 1, which suggests that there is some first-order autocorrelation in the data. This means that the current value of the returns is correlated with the previous value.

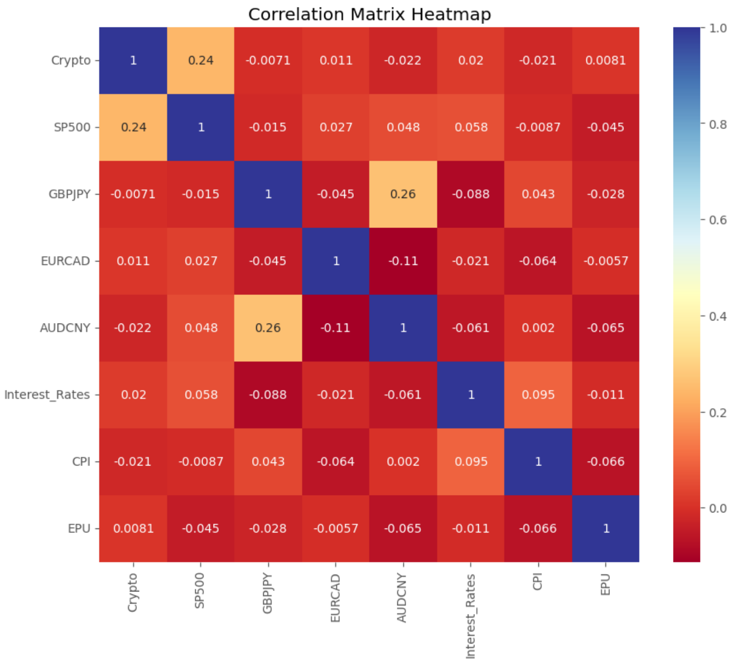


Figure 4: Correlation table of all variables.

The correlation table shows weak correlations among the variables. For example, the correlation coefficient between 'Crypto' and 'SP500' is 0.24. It might imply that the variables may not be very correlated in reality as they are measuring different things, or because they are not affected by the same factors. Moreover, the strength of the correlation coefficient depends on the scale of the variables. A correlation coefficient of 0.24 may be considered strong if the variables are measured on a small scale. The next section discusses the relationship between 'Crypto' and 'SP500' in detail.

6 Evaluation

In this section, a comprehensive analysis of the results obtained from the implementation of the proposed solution is presented. The focus is on the evaluation of the three research objectives: cointegration analysis of cryptocurrency and the stock market, cryptocurrency price prediction, and identifying the important macroeconomic variables. The significance of the findings is examined from both academic and practitioner perspectives.

6.1 Cointegration between the S&P BDM Cryptocurrency Index and the S&P500 Stock Index

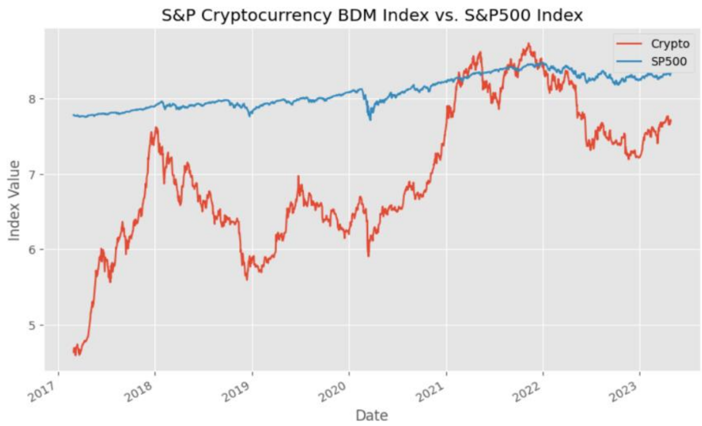


Figure 5: Closing prices of cryptocurrency and stock index in the last 6 years.

For the cointegration analysis, historical data of cryptocurrency prices and stock market indices are collected and pre-processed to handle missing values and ensure uniformity in the time series. The ADF test was utilised to detect a unit root and the original data is detrended to achieve stationarity at first difference. Next, the existence of a long-term equilibrium relationship would be verified by a series of cointegration tests as below:

Table 3: Cointegration test results.

Test	Results
Johansen test eigenvalues; Critical values (90%, 95%, 99%)	[0.11174122 0.09700297]; [[12.2971, 14.2639, 18.52], [2.7055, 3.8415, 6.6349]]
Cointegration rank	[0.11174122 0.09700297]
Engle-Granger test	t-statistic = 13.458, p-value = 0.000
VECM	See Table 4.

Table 4: VECM test results.

Coefficients	Standard errors	z-statistics	p-values
ec1 for Crypto	-0.4058	-13.150	0.000
ec1 for SP500	0.1428	18.651	0.000
beta.1	1.0000	0.000	0.000
beta.2	-5.0268	-26.128	0.000
const	-0.0009	-0.580	0.562

From the results, ‘Crypto’ and ‘SP500’ cointegrate according to the Johansen Test eigenvalues that are above the critical values. The cointegration rank further illustrated evidence that there are two cointegrating vectors between the two financial assets. The cointegration rank is an essential parameter to determine the long-term equilibrium relationship. The Engle-Granger supports the previous findings. To quantify the cointegrating relationship, the coefficients produced by VECM suggest a negative relationship. These coefficients are statistically significant as indicated by the corresponding z-statistics (-13.150 and 18.651) and p-values (both 0.000). Overall, the analysis suggests that there is a cointegrating relationship between 'Crypto' and the 'SP500', and this relationship is negative, implying that when the 'SP500' increases, 'Crypto' is expected to decrease in the long run, and vice versa.

6.2 Cryptocurrency Price Prediction

Table 5: Summary of the output of volatility models.

Model / Coefficients	ARCH (1)	ARCH (2)	GARCH (1,1)
Omega	2.1190e-03	1.7422e-03	1.6380
Alpha	0.0965	0.1915	0.0750
mu (constant)	3.3931e-03	2.8836e-03	0.3083

The constant parameter is positive for all three models, which indicates that the mean of the volatility process is positive. This means that the volatility of the 'Crypto' series is expected to be positive on average. Overall, the GARCH (1,1) model seems to be the best fit for the data.

Next, the accuracy of each predictive model is compared below:

Table 6: Model selection and evaluation of each predictive analysis (* denotes the lowest value).**

Model	MSE	MAE	RMSE	MAPE	R^2
ARIMA	0.14858	0.27773	0.38546	0.03654	-5.09392
VAR	0.00067***	0.02071***	0.02596***	0.88272	-13.87220
LSTM	0.00167	0.02958	0.04092	0.00396	0.93526
Naïve model	0.0012	0.0233	0.0351	0.00311***	0.9490***

- ARIMA:

The ARIMA model performs poorly with negative R^2 (-5.09392), indicating that the model does not explain the variation in the data at all. The MSE, MAE, and RMSE values are relatively high, suggesting a significant deviation of predicted values from the actual values. The negative means that the ARIMA model is not a suitable choice for predicting cryptocurrency prices.

- VAR(8):

The VAR model shows the lowest MSE, MAE, and RMSE values among the models, indicating that it has the smallest prediction errors. However, the negative R^2 value (-13.87220) suggests that the VAR model may not be capturing the variability in the data well, similar to the ARIMA model. The VAR model provides better predictions than ARIMA while considering the exogenous variables, but it may not be accurate enough for practical use due to the high MAPE and negative R^2.

- LSTM:

The LSTM model exhibits moderate MSE, MAE, and RMSE values, indicating reasonably accurate predictions compared to the actual data. The relatively low MAPE (0.00396) suggests that the percentage errors are small. The high R^2 value (0.93526) indicates that the LSTM model explains a significant portion of the variability in the data, suggesting a good fit.

- Naïve model:

The Naïve model, which serves as a baseline, exhibits competitive performance with the LSTM model. The MSE, MAE, and RMSE values are relatively low, indicating accurate predictions. The low MAPE (0.00311) suggests minimal percentage errors. The high R-squared value (0.9490) indicates that the Naïve model explains a substantial portion of the variability in the data, suggesting a strong fit.

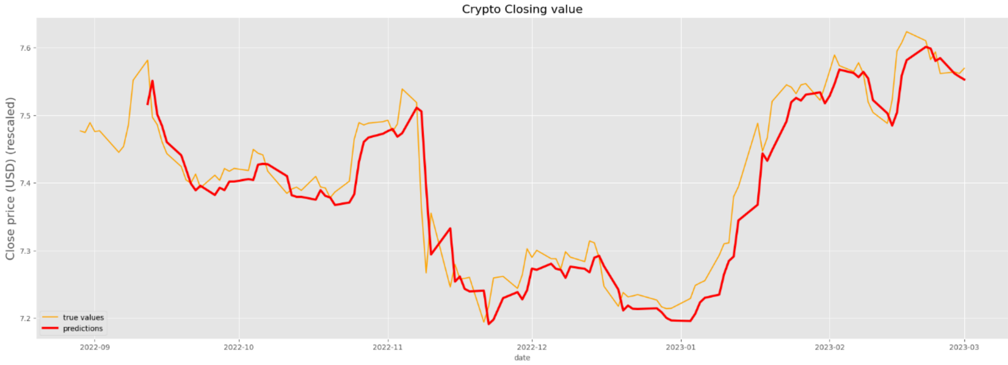


Figure 6: Cryptocurrency actual vs forecasted values using LSTM.

The Naïve model outperformed machine learning techniques for various reasons. First, the Naïve model works well when data points are strongly autocorrelated. The Naïve model's simplicity benefits datasets with simple patterns and correlations. The Naïve model's forecasting power for assets with random walk behaviour is restricted by its simplicity and lack of external influences or basic patterns. Thus, its projections are more likely to be impacted by chance than important insights, reinforcing the idea that using historical prices to anticipate extremely volatile and uncertain markets like cryptocurrency is not a realistic method.

6.3 Feature Importance Analysis

Table 7: Random Forest regressor output of the exogenous variables (* denotes significance).**

Feature	Importance
SP500	0.2002259***
GBPJPY	0.0654479
EURCAD	0.1510123***
AUDCNY	0.0837037
Interest_Rates	0.3114671***
CPI	0.0789576
EPU	0.1091853

The feature importance analysis using the Random Forest Regressor model reveals that the most influential feature in predicting cryptocurrency prices is ‘Interest_Rates’ (0.3115), followed by ‘SP500’ (0.2002). On the other hand, ‘GBPJPY’ is the least important (0.0654).

6.4 Discussion

The cointegration analysis in this study revealed a long-term connection between S&P Crypto BDM Index and the S&P500 Index. This finding is consistent with previous research by (Bouri, Kristoufek and Azoury, 2022) and (Jeris *et al.*, 2022), who also identified a significant relationship between cryptocurrency and stock markets. The correlation implies that there are limited diversification benefits, where cryptocurrencies are not an efficient hedge against stock market volatility. As cryptocurrencies and equities are often treated similarly, a mutual influence exists between the behaviour of both markets. The results highlight the need for caution when investing in cryptocurrency and the importance of understanding the relationship between cryptocurrency and the stock market.

The ARCH and GARCH analyses indicate tremendous cryptocurrency return volatility. When the market is turbulent, cryptocurrency returns tend to fluctuate more. These findings help risk-averse investors however, their conclusions may not be predictive as these models are based on historical data. The LSTM model's high accuracy and predictive power align with prior research by (Kim and Won, 2018; Ferdiansyah *et al.*, 2019; Zhang *et al.*, 2022) who concluded LSTM to be an effective method for predicting cryptocurrency and stock prices.

Unfortunately, the evaluation of predictive models for cryptocurrency price prediction uncovered intriguing observations. Classification machine learning was explored after conventional econometric models showed varied prediction ability. Logistic Regression, Random Forest Classifier, K Nearest Neighbours, and Support Vector Classifier had 0.53 accuracies. This outcome implies that the predictive accuracy of the constructed models is akin to a coin flip, highlighting the challenge in accurately forecasting cryptocurrency prices based on the selected exogenous variables.

The findings from our study contribute to the existing literature by highlighting the complexity of cryptocurrency price prediction. Our research aligns with previous studies (Kusumastuty *et al.*, 2019; Dimitriadou and Gregoriou, 2023) that have concluded there are no significant relationship between macroeconomic variables and cryptocurrency. Furthermore, our classification model findings further highlight the difficulties of using exogenous factors for price prediction. This adds to the debate surrounding cryptocurrency prices forecasts and highlights the importance of market dynamics.

The present research focused on certain exogenous variables, however exploring a wider collection of elements might improve prediction models. Additionally, sentiment analysis and real-time data streams may improve cryptocurrency price forecasts by collecting market sentiments and relevant occurrences. Furthermore, an investigation into the potential impact of regulatory changes and technological advancements on price prediction could provide valuable insights into the evolving landscape of cryptocurrency markets. Despite giving insights into cryptocurrency-stock market cointegration, cryptocurrency price predictions, and macroeconomic effect, the present architecture has disadvantages. First, the sample size may not convey the complexity of cryptocurrencies, limiting market behaviour detection. Second, effective prediction models like ARIMA and VAR may not completely reflect market dynamics, thus more powerful machine learning approaches like deep learning models may improve accuracy. Explore macroeconomic aspects beyond those investigated in this research to further understand market linkages. Longer periods enhance experiment robustness. To better understand market relationships, other macroeconomic factors beyond those examined in this study should be explored. Longer timeframes can improve experiment robustness. The present experiment helps explain the topic, but adding the enhancements might reveal more about cryptocurrencies and stock markets.

7 Conclusion and Future Work

In conclusion, the research embarked on a multifaceted exploration of the relationships between cryptocurrencies and stock markets with the central research question of understanding the volatility dynamics, price prediction, and the influence of macroeconomic factors.

This research yielded valuable insights into the intricate connections between cryptocurrencies and stock markets. Cointegration was effectively demonstrated between the two markets, indicating a long-term relationship due to volatility spillovers. This finding contributes to the expanding corpus of knowledge regarding the co-movement of these financial realms during market volatility. Additionally, our analysis of predictive models revealed challenges in accurately forecasting cryptocurrency prices based on specific exogenous variables. The consistent accuracy observed across classification models underscores the complexity of predicting cryptocurrency price movements using the selected set of factors.

The implications of this research underscore the evolving nature of cryptocurrency markets and their interactions with external factors. The findings shed light on the challenges of accurate price prediction and highlight the multifaceted dynamics that influence cryptocurrency and stock market relationships. However, the author acknowledges the limitations of this study, such as the potential omission of crucial exogenous variables and the inherent volatility of cryptocurrency markets. These limitations provide a foundation for further refinement and expansion of this research.

Future research efforts in this field have the potential to yield deeper insights and resolve the limitations identified in this investigation. Meaningful future work could explore the incorporation of additional exogenous variables, such as sentiment analysis and real-time social media data to enhance the accuracy of cryptocurrency price prediction models. The complex relationship between cryptocurrencies and stock markets could be further clarified by analysing the effect of regulatory changes and technological advancements on price dynamics.

This study concludes by shedding light on the multifaceted interactions between cryptocurrencies and stock markets. While the study has illuminated certain aspects of these relationships, it also highlights the complexity and challenges of accurate price prediction. As the cryptocurrency landscape continues to evolve, this research paves the way for future investigations that can build upon our work to enhance the comprehension of the intricate relationships between cryptocurrencies and stock markets.

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