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RESEARCH ON FACTORS INFLUENCING CRYPTOCURRENCY PRICES

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ABSTRACT

Cryptocurrencies are plagued by high risk due to its volatility and rapid reaction to influence from external factors. This research, aiming to contribute to the studies made in this event, explores the potential relationship between ten major cryptocurrencies and market factors and assets: stocks, oil, gold, inflation rates, and level of interest (buzz). The motivation for the study was to cast a wider net in terms of the cryptocurrencies, stock market indices, and regions investigated, resulting in findings that could be corroborated in previous research as well as potential new contributions and implications. The study applies a regression analysis approach to identify existing relationships between the digital assets and selected factors, as the process is efficient for correlation modeling. Statistically sound results are obtained for seven of the 10 cryptocurrencies this study covers. Some key findings are the pre-existing notion that the S&P 500 is positively correlated to cryptocurrencies and a lesser explored avenue on the spillover effects of Asian stock indices KOSPI and S&P/HKEX LC. Second, a negative relationship is observed about Oil, solidifying the perspective on the influence of increasing oil prices on cryptocurrency productivity. Additionally, the study evidences the potential hedging properties of cryptocurrencies against inflation, especially in the United States and the United Kingdom.

KEYWORDS: ***Cryptocurrency Prices, Regression Analysis, Correlation Analysis, Stock Market, Market Factors, Digital Assets***

1. INTRODUCTION

Cryptocurrencies have recently attracted widespread attention as a decentralized and innovative digital currency. By the end of 2022, the $2 trillion crypto economy had over 300 million stakeholders with currencies, such as Bitcoin, Ethereum, Tether, Binance coin, and USD Coin, dominating the market, propelled by Web3 innovations, and increasing adoption of non-fungible tokens (Hyatt, 2022). The top 10 cryptocurrencies in the market as of May 2023 (CoinMarketCap, 2023) are the targeted crypto assets for this research. However, the industry's rapid growth is plagued by significant fluctuations in prices, with some cryptocurrencies experiencing dramatic booms and busts in a matter of days or weeks, behavior that is atypical to other financial markets (Wigglesworth and Szalay, 2021). It is attributed to various internal technical factors such as hash blocks, supply and demand volume, mining costs, and external economic and geopolitical factors such as capitalization, inflation rates, interest rates and policy regulations, and war (Jones, 2023).

This study aims to investigate the intrinsic correlation between 10 different cryptocurrencies and external factors, i.e., stock market indices, oil and gold prices, inflation rates of the top 10 countries that mine cryptocurrency most, and level of interest (buzz), using ordinary least squares (OLS) regression to estimate the relationships.

There is a wide array of research concerning the various factors influencing cryptocurrency prices. The previous research, however, focused wholly on individual cryptocurrencies or combined trends across the entire cryptocurrency market rather than the interactions between different market drivers and arrays of individual cryptocurrencies. However, with the market ever-growing and the rise of several vital crypto assets that are growing at similar rates Bitcoin showed in its inception, it would be insightful to cast a wider net on the cryptocurrencies analyzed for studies hence the primary motivation for this research.

This study is therefore built on the assumption that different market drivers would display different significance in price movement dependent on the cryptocurrency and seeks to explore whether this is true. Hence, this research loosely applies a similar approach to a paper by Dubey (2022) that explores the fundamental, financial, macroeconomic, and technical variables influencing Bitcoin prices.

This study narrows down on selected stock indices, inflation rates, Google search trends, oil prices, and gold prices as the selected factors to evaluate on correlation with cryptocurrency price. A regression analysis approach examines the relationships and is iterated over the ten cryptocurrencies' closing prices. Previous studies related to the correlation between stocks and cryptocurrency focused on the NASDAQ index and the Standard and Poor's 500 (S&P 500) index's effect on price movement. While the latter is included in this study, the research takes a slightly different approach by examining the representative stock indices of the top 10 countries that mine cryptocurrency the most as of January 2023, hoping to uncover new insights into the complex dynamics of the crypto market. These countries are namely the United States (U.S.), South Korea, Japan, Singapore, the United Kingdom (U.K.), Australia, Hong Kong, Canada, China, and Switzerland (Statista, 2023).

This study aims to answer the following research questions. RQ1: What factors are most strongly correlated with cryptocurrency price trends? RQ2: Do the same factors impact different cryptocurrencies similarly, or do different cryptocurrencies have unique drivers of price trends? RQ3: Are there any cross-country or cross-regional effects on cryptocurrency price trends? Regarding the three research questions, based on the findings of the results, patterns of similarities or differences in how the selected factors affected the cryptocurrencies would provide avenues for further research.

The results of this study will expand knowledge on lesser studied cryptocurrencies and contribute to the existing research on the cryptocurrency market and its behavior, which should be helpful to academic researchers and industry experts. Additionally, the regression approach may provide grounds for further analysis and applications of other prediction tools to help forecast future research. Lastly, significant observations related to the RQ3 may provide insight into whether specific regional markets influence the crypto market, which could be helpful to investors and stakeholders.

2. LITERATURE REVIEW

This section reviews key findings from previous research on cryptocurrency price trends and the factors influencing them.

2.1 Theoretical Background

Stock market vs cryptocurrencies: Over time, more investors and venturers have begun to consider cryptocurrencies as an asset class, with many comparing them to stocks due to their fundamental similarities and differences. Additionally, the relationship between the two is gaining further interest due to the increased integration between cryptocurrencies and traditional financial assets (Bouri et al., 2018a).

The first similarity that puts these two markets on the same playing field is the risk of investing in each. Their price movements are volatile; hence investors need to constantly track price changes and be wise and timely in deciding to buy, hold and sell these assets. Ironically, in this similarity lies one of the most enormous differences. While stock market prices can plunge in a day, it is rare to experience total losses in one go. Cryptocurrencies, however, are more violent in their fluctuations and require intense monitoring to avoid complete losses.

Another common denominator is that both assets follow the basic principle of supply and demand: prices increase when demand exceeds supply. In the context of the stock market, companies decrease the supply of available stock shares by delisting and buying back their stock to increase prices in the event of demand not decreasing (Investopedia, 2022). Similarly, available cryptocurrency supply volumes in the crypto market are usually selectively limited, leading to increased demand and price.

More recently evidenced by the COVID-19 pandemic in 2020 is the significance of macro events on investment prices. Due to the economic stress endured in different markets, especially in the initial months, historically significant and rapid declines were displayed across all sectors. It could be to several studies, such as the study by Uddin et al. (2022), who investigated the interconnected dynamics caused by the pandemic that resulted in a significant positive reliance among markets hence a tendency to display co-movements across worldwide financial markets. Bouri et al. (2022) also identified co-movement between Bitcoin and S&P 500 to be moment dependent, their study evidencing more robust interconnections during the COVID-19 outbreak. Nguyen (2022) suggested the significance of the market index S&P 500 about Bitcoin returns during this period while cryptocurrencies displayed dynamic conditional correlations amongst themselves, as Yan et al. (2022) portrayed.

It is based on this that the first hypothesis is determined:

H_1: A stock market index has a positive effect on cryptocurrency prices.

Interconnection to trade commodities: There are various trade commodities exchanged worldwide. In this study, Oil and Gold are the most significant; hence only literature about these was examined and discussed. The interconnection between trade commodity prices and cryptocurrency price movements is a topic of ongoing debate and research. The operational costs for mining cryptocurrencies use significant amounts of energy often covered by trade commodities such as Oil and Gold. Hence, simple inferencing would gather that increasing energy prices would increase operational costs, leading to a decreased supply of cryptocurrencies driving up prices.

Trade commodities, especially Gold, tend to be more stable in terms of price trends compared to cryptocurrencies, hence are often referred to as safe-haven assets, unlike cryptocurrencies which portray high volatility and risk. It means that even in times when the downturn of markets prolongs, gold prices act as a form of insurance for investors (Harmston, 1998). It alone would undermine any relationship between the two, and this has always been the consensus that the prices of Gold and cryptocurrency are essentially uncorrelated. However, due to the underlying macroeconomic factors such as inflation and monetary policy, Oil and gold prices have shown a tendency to display short-term or spillover effects on the prices of cryptocurrencies from time to time.

Regarding the concept introduced above, in March 2023, a historically strong correlation between Bitcoin and Gold emerged as trends displayed both assets moving in similar directions throughout the month. According to Beganski (2023), the correlation has been around 50% by Kaiko, a blockchain analytics firm. This observation is highly attributed to the changing view of investors recognizing that cryptocurrencies have the potential to act as a store of value hence dimming the perception that they are not able to behave as safe-haven assets and is further supported by Bouri et al. (2017) in exploring the properties of Bitcoin. It is assumed this will be a more observable trend across various cryptocurrencies as the market grows. Additionally, there is the emergence of "gold-backed" cryptocurrencies which are digital coins indexed to the value of Gold, such as X8X and HelloGold, created to increase efficiency in returns (Aloui et al., 2021).

This study will hence explore the second hypothesis:

H_2: Gold prices have a positive effect on cryptocurrency prices.

About the relationship between Oil and cryptocurrencies, some research suggests that as economic policies become vaguer and more uncertain, the correlation between oil prices and cryptocurrencies becomes more evident (Cheng and Yen, 2020). Additionally, Jareño et al. (2021) investigated the response of the cryptocurrency market to oil price shocks using a Nonlinear Autoregressive Distributed Lard (NARDL) that suggested the two markets especially linked during periods of economic turbulence, i.e., COVID-19. Kumah and Odei-Mensah (2022) explored the significance of oil prices and cryptocurrencies across multiple currencies, resulting in positive and negative connections.

This study aims to determine what sort of correlation there exists between oil prices and cryptocurrencies. The third hypothesis hence formulated as follows:

H_3: Oil prices have a positive or negative effect on cryptocurrency prices.

Inflation rates and cryptocurrency price dynamics: Researchers and market experts seek to understand the potential influence of inflation on the value and the adoption of digital assets. Studies have provided conflicting findings; for instance, Ciaian et al. (2015) found no significant relationship between inflation and Bitcoin prices, while Bouri et al. (2018b) employed a copula-based approach to investigate the dynamic relationships between inflation (global financial stress) and Bitcoin resulting in a significant correlation between the two though directional predictability power was low.

Inflation, often expressed as a percentage, describes the general increase in the prices of goods and services over time, leading to a decrease in the purchasing power of a currency. Hence, experts argue that cryptocurrencies have properties that deem them resistant to inflationary pressures. It is supported by various studies, such as Cheah and Fry's (2015) paper that highlights the scarcity and decentralized nature of Bitcoin as factors that enable it to act as a store of value and hedge against inflationary pressures.

Therefore, since it is evidenced that cryptocurrencies indeed portray this resistance during periods of rising inflation, it is sensible for investors to deem cryptocurrency an attractive asset, leading to increased demand and potentially increasing prices. While the correlation is not straightforward, the assumption suggests that the correlation between the two is worth exploring. Empirical studies to quantify the dynamic dependence of the U.S., eurozone, U.K., and Japan Bitcoin market returns and recorded unexpected inflation by Matkovskyy and Jalan (2021) found that the USD Bitcoin market performs worse with inflation. The study by Conlon et al. (2021), however, contradicts this observation, finding there is a brief positive relationship between forward inflation expectations and both Bitcoin and Ethereum when applying continuous wavelet transform (CWT) to quantify the magnitude, direction and any lead-lag effects between the two concepts.

From this, we hypothesize the following relationship:

H_4: Inflation rates have a positive effect on cryptocurrency prices.

Media interest significance in cryptocurrency price movements: It is argued that digital currency prices are driven by the investors' faith in perpetual growth hence emphasizing the importance of investors' sentiment and its influence on the crypto market. Interestingly, however, most research shows that the volume of interest and sometimes even the platform the cryptocurrency is discussed on are more significant than the actual sentiment towards cryptocurrency. Kristoufek (2013) uses Google trends and Wikipedia to represent investor sentiment towards Bitcoin, finding a strong positive correlation between the price of Bitcoin and search trends. Additionally, they add that the relationship is bidirectional, which means that when Bitcoin prices go up, there is also an increase in search queries. Another exciting take was that when a cryptocurrency market is declining, it is more likely to respond to positive social sentiment, evidenced by Kim et al. (2021) using a hidden Markov model (HMM) to assess cryptocurrency market shifts influenced by social sentiment during bull and bear markets (Carta, 2023).

Mai *et al*. (2016) examine the impact of social media on Bitcoin performance, finding that messages on internet forums cause significant changes in future Bitcoin measures at a daily frequency, while microblogs are more potent in displaying significance at an hourly frequency. They further expand their study by analyzing the magnitude of how impactful internet forum messages are compared to tweets to future Bitcoin value, finding that the former has a more substantial impact (Mai et al., 2018). This implication is also supported by Rothman and Yakar (2019), who find that volumes of exchanged posts, especially on Reddit and Telegram, in comparison to Twitter posts, can predict fluctuations in Bitcoin prices (Rothman and Yakar, 2019).

Another field of interest in this area is the role of misinformation in price volatility. Lee and Jeong (2023) analyzed a large corpus of 500 cryptocurrencies concerning 36,572 media coverages, finding that cryptocurrency price volatility increased even for minor coins, even if the news was not directly related. They argued that increased news coverage on cryptocurrency markets without a proper understanding of their fundamental value influenced the volatility of both significant and minor crypto coins.

Thus, the fifth hypothesis is derived on the premise that an increase in Interest (Google search trends) would lead to an increase in cryptocurrency price.

H_5: Google search trends have a positive effect on cryptocurrency prices.

2.2 Conceptual Framework

This study seeks to explore the potential cause-effect relationship between independent variables; stock market prices, inflation rates, oil prices, gold prices, and the level of interest, proxied by Google search trends, and the dependent variable; cryptocurrency price, through the five hypotheses. The process is to be iterated over the selected ten cryptocurrencies to compare how the independent variables can have varying impacts on the dependent variable of the crypto coin. Figure 1 illustrates the conceptual framework followed by the study.

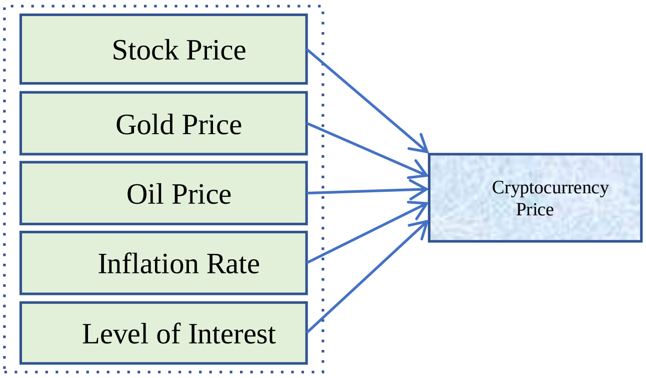

Figure 1. Conceptual Framework

3. RESEARCH METHODOLOGY

3.1 Research Philosophy

This study is an exploratory analysis aiming to support or challenge previous findings in the literature and contribute to discovering new patterns and correlations between the selected variables. It follows a quantitative methodology and combines both inductive and deductive reasoning (Kenaphoom, 2021).

This research takes on positivism as the main philosophy behind it. Positivism applies logical and mathematical approaches to analyze data and test hypotheses to enforce an idea, observation, or establish causal relationships (Saunders et al., 2019).

3.2 Overview of Research Methodology

The study is applying linear regression principles to check for relationships between the array of variables chosen for the study using the IBM SPSS software platform to perform the analysis. For the data collection, relevant historical data was obtained from a combination of multiple public datasets retrieved from reliable sources and web scraping techniques employed to build the final corpus for the study. The goal was to minimize the number of missing values in the dataset hence the need to cross-reference across multiple sources.

The following outlines the steps taken in the study: 1) Data Collection: Historical data was collected from various sources, categorized as monthly observations, and compiled into one dataset. 2) Data Cleaning and Preparation: This stage involves checking for missing values, outliers, and duplicates, removing irrelevant variables, and transforming variables as necessary. 3) Correlation Analysis: This helps determine the associations between variables, providing insight into the direction (positive or negative) and degree of their correlation. 4) Regression Analysis: The study seeks to explore the influence of market factors across a selected array of 10 cryptocurrencies. Multiple regression analysis is employed and iterated for each cryptocurrency. 5) Testing for Regression Assumptions: The results of the regression analysis are subjected to a range of tests, i.e., linearity, normality, multi-collinearity, and heteroscedasticity tests, to ensure soundness in observations and inferences. 6) Discussion of Findings: Hypothesis testing is done, and the study findings are discussed in the context of previous research and theoretical frameworks. Additionally, the limitations and implications of the study are outlined.

3.3 Research Design

3.3.1 Selection of Variables and Collection of Data

The initial approach to carry out the regression analysis was to target features believed to have a high correlation to cryptocurrencies while focusing on factors that ideally reside outside the scope of each, i.e., external factors, to analyze the effects across multiple currencies; hence the settlement on what commonly referred to as market-related factors.

For the application of the linear regression model, the research will use closing price data of the top 10 cryptocurrencies with the highest stake hold on the crypto market, the most significant stock market indices, as well as inflation rates of the ten countries with the highest mining volume as of March 2023, trade commodity prices of Gold and Oil, and Google search trends related to the selected cryptocurrencies. This study takes observations measured monthly to accommodate inflation rates and Google search trends. Table 1 describes the data variables' classification into dependent and independent variables and their descriptions and sources.

Table 1. Overview of data variables

Type	Variable	Description	Source
Dependent	Cryptocurrency Closing price	Daily closing price (USD) of top 10 cryptocurrencies as of March 2023	Investing.com/ Coinmarketcap.com
Independent	Inflation rates	Inflation rates (by country) of Top 10 countries investing in cryptocurrency (%)	FXEMPIRE.com
Independent	Stock Market Prices	Stock Exchange rates (by country) of the Top 10 countries investing in cryptocurrency	Investing.com
Independent	Oil Prices	Oil price index	Investing.com
Independent	Gold Prices	Gold price index	Investing.com
Independent	Google Trends	Google Search Trends	Trends.google.com

Most of the variables were quickly downloadable as open-source datasets. However, to mitigate missing values, especially concerning total market capitalization and inflation rate, web scraping techniques were employed using the web browser Inspect tool and going through the HTML response body to retrieve the data values.

3.3.2 Data Cleaning and Preparation

During data collection, the ten selected stock indices and oil and gold prices had a lot of missing data at uniform intervals, as there were no rates during weekends and holidays. Removing the rows would have affected the integrity of the research; hence, interpolating the values was a viable decision. Linear interpolation was employed as it is helpful in curve fitting using linear polynomials built on the coordinates of two known points.

Logarithmic transformation of variables conducted to handle situations with a non-linear relationship between the independent and dependent variables (Benoit, 2011). This research took the log-linear approach where only the dependent variable transformed the form log10 (Yi). Therefore, the regression equations obtained would be interpreted differently from the usual linear regression.

3.3.3 Correlation and Regression Analysis

Concerning the research objectives, correlation analysis was applied to establish the strength of the associations between variables. SPSS software provides
functionality to derive a correlation matrix used in this study to not only check for relationships between dependent and independent variables but also as a valuable tool to flag correlations between the independent variables, which would undermine the regression process. The matrix allows for identifying positive, negative, and weak/zero correlation hence was a vital tool for this research. Additionally, it could provide avenues for future research by flagging other strong correlations that were not within the scope of this study.

Regression analysis, in particular OLS regression, is defined as an optimization strategy helpful in the construction of linear models by finding unbiased value estimates that help influence or explain a dependent variable (Alto, 2023). Through the SPSS built-in regression functionality, three main tables relevant to this research are focused on. They provide a model summary that includes the adjusted R-Squared value (R2), the Analysis of Variance (ANOVA) summary that gives the p-value portraying whether the model is significant or not, and the regression coefficients (WikiBooks, 2010).

3.3.4 Testing for Regression Assumptions

Linearity is a test to determine whether the relationship between independent and dependent variables follows an identifiable linear trend and is required in correlation and linear regression analysis. This study used the Normal P-P (Probability-Probability) plot of standardized Residuals to test this assumption (SPSS Tests, 2015; Statistics Solutions, 2023).

Normality testing for OLS is carried out on the residuals of the regression model, which can be defined as the differences between estimated regression points and the observed values of the dataset. SPSS allows Testing to be carried out using a Normal Q-Q (Quantile-Quantile) plot of standardized residuals and the Shapiro-Wilk normality test (EZ SPSS Tutorials, 2023; Shapiro and Wilk, 1965).

Autocorrelation measures the relationship between a variable's current value and its past values, observed commonly in time-series models where researchers use it to estimate how much past observations, for example, in price, would influence future observations (Smith, 2023). The Durbin-Watson test was used for this assumption (Durbin and Watson, 1971). The general rule of thumb is that values in the range of 1.5-2.5 are relatively normal, which was also applied to this study (Field, 2009). This study applied a method suggested by Granville (2019).

Multicollinearity is defined as the event where two or more independent variables in a data frame have a high correlation with one another in a regression model (Bhandari, 2020). It is attributed to arise when using OLS regression, its presence leading to the estimated regression coefficient becoming large and unpredictable, rendering unreliable inferences about the effects of the predictor variables on the response variable. The study applies the Variance Inflation Factor (VIF) and tolerance values to detect this anomaly. Once detected, feature selection is carried out to redefine the dataset to a subset of predictor features not highly correlated with each other. This study employed the Glejser test (Glejser, 1969) for homoscedasticity.

4. EMPIRICAL ANALYSIS

4.1 Description of Data

The analysis explores how stock market indices, oil price, gold price, inflation rates, and level of interest, proxied by Google search trends, may affect ten cryptocurrency prices. The study hence focuses on Bitcoin, Ethereum, Tether, Binance Coin, USD Coin, Ripple, Cardano, Dogecoin, Solana, and Polygon monthly closing prices as the dependent variable. Furthermore, ten stock indices were thoughtfully selected to serve as respective indicators of their country's stock market conditions detailed as follows: Standard and Poor's 500 (S&P 500), Korean Composite Stock Price Index (KOSPI), Japan NI225 or Nikkei Stock Average (Nikkei 225), Financial Times Stock Exchange Group (FTSE) Strait Times Singapore, Financial Times Stock Exchange 100 Index (FTSE 100), S&P/ASX 200, Hong Kong Exchanges and Clearing Limited LargeCap (S&P/HKEX LC), S&P Toronto Stock Exchange Composite (S&P/TSX Composite), Shanghai Composite, and Swiss Market Index (SMI). The subsequent subsection gives further elucidation on the variables used in this research.

Data labels and variables: This is to provide an easy understanding to the reader of what the variables analyzed represent. Table 2 describes the variables representing the dependent variable, cryptocurrency price, and independent variables, i.e., stock market indices, inflation rate, level of interest, Gold, and Oil.

Table 2. Data variables and respective labels

Dependent Variable: Cryptocurrency Price

Label	Variable
Bitcoin Price	BTC_Close
Ethereum Price	ETH_Close
Tether Price	USDT_Close
Binance Coin Price	BNB_Close
USD Coin Price	USDC_Close
Ripple Price	XRP_Close
Cardano Price	ADA_Close
Dogecoin Price	DOGE_Close
Solana Price	SOL_Close
Polygon Price	MATIC_Close

Independent Variable: Inflation Rate

Label	Variable
US Inflation Rate	US_INF
South Korea Inflation Rate	KR_INF
Japan Inflation Rate	JP_INF
Singapore Inflation Rate	SG_INF
UK Inflation Rate	UK_INF
Australia Inflation Rate	AU_INF
Hong Kong Inflation Rate	HK_INF
Canada Inflation Rate	CA_INF
China Inflation Rate	CHN_INF
Switzerland Inflation Rate	CH_INF

Independent Variable: Stock Market

Label	Variable
S&P 500	US_Stock
KOSPI	KR_Stock
Nikkei 225	JP_Stock
FTSE Strait Times Singapore	SG_Stock
FTSE 100	UK_Stock
S&P/ASX 200	AU_Stock
S&P/HKEX LC	HK_Stock
S&P/TSX	CA_Stock
Shanghai Composite	CHN_Stock
SMI	CH_Stock

Independent Variable: Gold

Label	Variable
Gold Futures	GOLD

Independent Variable: Oil

Label	Variable
Crude Oil WTI Futures	OIL

Independent Variable: Level of Interest

Label	Variable
Bitcoin Search Trend	BTC_Trend
Ethereum Search Trend	ETH_Trend
Tether Search Trend	USDT_Trend
Binance Coin Search Trend	BNB_Trend
USD Coin Search Trend	USDC_Trend
Ripple Search Trend	XRP_Trend
Cardano Search Trend	ADA_Trend
Dogecoin Search Trend	DOGE_Trend
Solana Search Trend	SOL_Trend
Polygon Search Trend	MATIC_Trend

Descriptive statistics of the entire corpus: Bitcoin, Ripple, and Dogecoin recorded 114 monthly closing prices, the maximum N of the dataset; Tether had 102 valid inputs, Ethereum 94, Binance Coin 70, and Cardano 68, while USD Coin, Polygon, and Solana recorded 56, 49, and 38 valid inputs respectively. The differences in inputs were not much cause for worry as each regression was run separately for each cryptocurrency, allowing all corresponding inputs to be tested.

Stock indices and Gold and Oil each recorded 112 valid inputs, and each country's inflation rates each recorded 111 valid inputs. While examining the data for listwise missing values, it was decided to remove the Australian inflation rate (AU_INF) as it is measured quarterly per year, introducing too many missing values at irregular intervals that could not be fixed through interpolation or imputation. The rest of the study hence proceeds without this variable. Lastly, all the crypto assets recorded 113 valid inputs for Google search trends with the exemption of Polygon, Ripple, and Tether, which resulted in 96, 78, and 73 valid inputs, respectively.

4.2 *Testing of OLS Assumptions*

4.2.1 Handling of Multicollinearity

The results of correlation testing showed that not only did the predictor variables show a significant relationship with the dependent variables, but also among themselves introducing multicollinearity, which would lead to significant changes in the estimated coefficients if slight modifications were made to the dataset. Only variables with VIF<10 and tolerance>0.1 to remedy the anomaly were considered for the study. The collinearity diagnostics are included in the ANOVA results of the final models for each cryptocurrency in the following section.

4.2.2 Linearity Assumption Test

With the exemption of Tether, the assumption of linearity was validated across the other cryptocurrencies, 8 of which upheld the condition. USD Coin indicated evidence of non-linearity; hence this study could not assume linearity. The test was carried out by examining each cryptocurrency's normal P-P plot of standardized residuals, with the valid 8 having the plotted residuals falling along the line of equality. In the case of the USD Coin, many of the residuals fell away from the line, hence rejecting the hypothesis that the regression model was linear. A side-by-side comparison with the valid P-P plot for Bitcoin is shown in Figure 5. The remaining plots are presented in the Appendix I section of this paper.

In summary, Bitcoin, Ethereum, Binance coin, Ripple, Cardano, Dogecoin, Solana, and Polygon satisfied the linearity assumption. Moreover, USD Coin did not satisfy the assumption, and Tether was not tested on the assumption as no significant regression model was obtained.

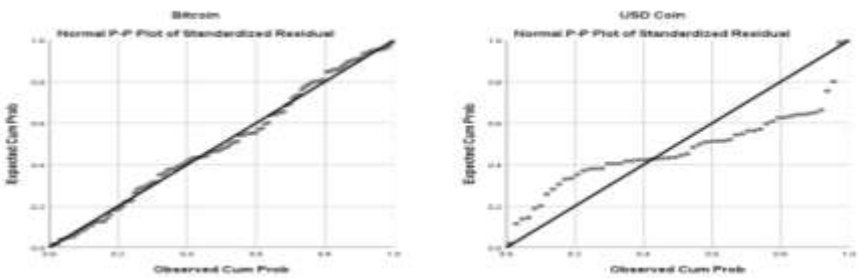

Figure 5. Normal P-P plots of residuals for Bitcoin and USD Coin

4.2.3 Normality Assumption Test

Three tests were conducted to test the assumption of normality. Table 3 presents the statistical test results. The Kolmogorov-Smirnov (Smirnov, 1948) test is used to verify whether a population follows a hypothetical distribution, in this case, a normal distribution. The null hypothesis assumed the data comes from the specified distribution being tested, only accepted if the p-value>0.05. The Shapiro-Wilk test would also assume normal distribution if the p-value exceeds 0.05.

Bitcoin, Ethereum, USD Coin, Ripple, Dogecoin, Solana, and Polygon tests on normality were conclusive in that with the exemption of USD Coin, normality was assumed for the six cryptocurrencies. USD Coin showed evidence of violating the assumption, later verified by checking the Normal Q-Q of Standardized Residuals for the distribution illustrated in Figure 6.

In the case of Binance coin and Cardano, contradicting results were obtained for the two tests leading to further verification through examination of their respective Q-Q plots. The verdict based on the observed shape suggested normality in the distribution; hence, the Binance coin and Cardano also satisfied the assumption. Appendix II presents Q-Q plots for the remaining six cryptocurrencies.

Therefore, the assumption of normality is met by all the cryptocurrencies with the exemption of USD Coin and Tether.

Table 3. Normality tests

	Tests of Normality						
		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Bitcoin	Standardized Residual	0.05	111	.200*	0.987	111	0.383
Ethereum	Standardized Residual	0.079	93	0.191	0.98	93	0.157
Binance	Standardized Residual	0.083	69	.200*	0.964	69	0.042
USD coin	Standardized Residual	0.266	56	0	0.622	56	0
Ripple	Standardized Residual	0.054	111	.200*	0.992	111	0.781
Cardano	Standardized Residual	0.076	67	.200*	0.951	67	0.011
Dogecoin	Standardized Residual	0.046	111	.200*	0.992	111	0.808
Solana	Standardized Residual	0.083	37	.200*	0.967	37	0.323
Polygon	Standardized Residual	0.07	48	.200*	0.982	48	0.656
*. It is a lower bound of the true significance.							
a. Lilliefors Significance Correction							

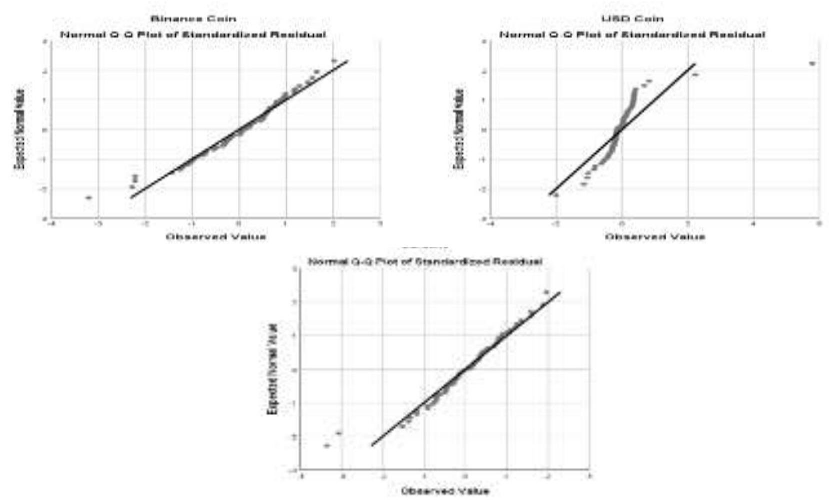

Figure 6. Normal Q-Q plot for Binance coin, USD Coin, and Cardano

4.2.4 Heteroskedasticity Test

This table focuses on the 'Sig.' values related to each independent variable forming the regression models. The cut-off value is p>0.05, for which the null hypothesis checking for the presence of heteroskedasticity is rejected, and it is assumed there is homoscedasticity. Analysis was carried out on 9 out of the ten cryptocurrencies with the exemption of Tether, as it did not result in a valid regression. Eight coin-related regressions met this assumption after analysis through the Glejser test (Glejser, 1969), whose results are portrayed in Table 4, or through further tests using the Breusch-Pagan method (1979). Binance coin failed to meet this assumption after validation using both tests.

Table 1. Heteroskedasticity tests

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
Bitcoin	(Constant)	-0.127	0.094		-1.347	0.181
	BTC_Trend	0	0.001	-0.104	-0.741	0.46
	CHN_INF	-0.002	0.008	-0.028	-0.267	0.79
	CHN_Stock	3.35E-06	0	0.02	0.163	0.871
	HK_INF	0.019	0.007	0.35	2.871	0.005
	HK_Stock	4.12E-06	0	0.283	1.861	0.066
	OIL	0	0.001	-0.053	-0.381	0.704
	UK_INF	0.002	0.005	0.09	0.503	0.616
	US_Stock	2.01E-05	0	0.222	1.194	0.235
Ethereum	(Constant)	0.622	0.259		2.403	0.018
	KR_Stock	0	0	0.263	0.982	0.329
	HK_Stock	-8.74E-06	0	-0.301	-1.869	0.065
	CHN_Stock	-3.33E-05	0	-0.057	-0.402	0.688
	GOLD	0	0	-0.249	-1.578	0.118
	OIL	-0.003	0.002	-0.318	-1.487	0.141
	UK_INF	0.007	0.011	0.135	0.61	0.544
	ETH_Trend	0.003	0.002	0.333	1.536	0.128
Binance Coin	(Constant)	0.785	0.148		5.31	0
	US_Stock	0	0	-0.828	-3.857	0
	KR_INF	0.024	0.013	0.261	1.832	0.071
	BNB_Trend	0.003	0.001	0.395	2.068	0.043
USD Coin	(Constant)	0.007	0.003		2.286	0.026
	CHN_Stock	-1.53E-06	0	-0.208	-0.898	0.373
	CH_Stock	1.24E-07	0	0.059	0.267	0.79
	GOLD	-1.55E-06	0	-0.164	-0.821	0.416
Ripple	(Constant)	0.244	0.132		1.847	0.067
	US_Stock	-9.31E-05	0	-0.384	-2.242	0.027
	UK_INF	0.018	0.011	0.252	1.619	0.108
	HK_Stock	7.88E-06	0	0.202	1.478	0.142
Cardano	(Constant)	0.031	0.284		0.108	0.914
	CHN_Stock	0	0	0.627	4.107	0
	CH_Stock	-9.56E-05	0	-0.681	-3.449	0.001
	US_INF	0.009	0.01	0.143	0.92	0.361
	ADA_Trend	0	0.001	0.053	0.349	0.728
Dogecoin	(Constant)	0.139	0.106		1.31	0.193
	US_Stock	-2.46E-05	0	-0.134	-0.639	0.524
	KR_Stock	6.80E-05	0	0.157	0.898	0.371
	UK_INF	-0.005	0.007	-0.099	-0.761	0.448
Solana	(Constant)	0.001	0.228		0.004	0.997

	JP_Stock	7.60E-06	0	0.173	0.83	0.413
	CH_INF	-0.016	0.015	-0.222	-1.064	0.295
	SOL_Trend	-1.34E-05	0.001	-0.003	-0.015	0.988
Polygon	(Constant)	0.11	0.171		0.643	0.524
	KR_Stock	-1.88E-05	0	-0.048	-0.293	0.771
	OIL	0.004	0.003	0.49	1.276	0.209
	US_INF	-0.023	0.022	-0.41	-1.078	0.287

Additional tests for Heteroskedasticity In the case of Bitcoin, Binance coin, Ripple, and Cardano, results from the Glejser test suggested the presence of heteroskedasticity in the regression models. An additional Breusch-Pagan test for Heteroskedasticity (1979) was carried out on the derived models to assess this further. The tests on Bitcoin, Ripple, and Cardano indicated a lack of evidence of heteroskedasticity, as p-values were more than 0.05. Homoscedasticity was assumed as a result; hence the derived regression models were deemed valid to continue the discussion—tables 5, 6, and 7 present the results.

Table 5. Breusch-Pagan test for Bitcoin

Breusch-Pagan Test for Heteroskedasticity [a, b, c]		
Chi-Square	df	Sig.
1.204	1	.273

a. Dependent variable: lnBTC_Close
b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.
c. Predicted values from design: Intercept + US_Stock + UK_INF + HK_Stock + BTC_Trend + CHN_INF + CHN_Stock + HK_INF + OIL

Table 6. Breusch-Pagan test for Ripple

Breusch-Pagan Test for Heteroskedasticity [a, b, c]		
Chi-Square	df	Sig.
.157	1	.692

a. Dependent variable: lnXRP_Close
b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.
c. Predicted values from design: Intercept + US_Stock + UK_INF + HK_Stock

Table 7. Breusch-Pagan test for Cardano

Breusch-Pagan Test for Heteroskedasticity [a, b, c]		
Chi-Square	df	Sig.
.215	1	.643

a. Dependent variable: lnADA_Close
b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.
c. Predicted values from design: Intercept + CHN_Stock + CH_Stock + US_INF + ADA_Trend

4.3 OLS Regression Analysis

This section discusses the results of the multiple regressions between the dependent and independent variables in detail. All the independent variables with significant correlation to the respective coins were included in the initial regression, after which the regressions were iterated to handle variables indicating multicollinearity resulting in the final regression models presented in this section. The t-test was used to test the statistical significance of the individual independent variables on each coin, allowing for hypothesis testing, while the F-test was used to test the statistical significance of the model derived. All the regression results discussed in the following sections displayed evidence of a lack of autocorrelation, each with a Durbin-Watson value falling in the acceptable 1.5-2.5 range recommended by experts.

The following sections present and discuss the results of each cryptocurrency. However, Tether, Binance Coin, and USD Coin are not discussed in depth due to the violation of regression assumptions discussed in the previous section.

4.3.1 Bitcoin

In the case of Bitcoin, a cumulative of 111 observations was used to derive the regression results. The results of the F-test indicated a significant relationship between Google search trends related to Bitcoin, the inflation rate in China, Hong Kong, and the United Kingdom, Oil and Shanghai Composite, S&P 500, and S&P/HKEX LC stock indices. The adjusted R^2 value of 0.97 indicated that these variables could explain 97% of the variation in Bitcoin closing prices, while 3% of the variation is explained through factors not captured by this study.

Based on the coefficients derived, a statistically significant positive relation was implied between the dependent variable, Bitcoin closing prices, Google search trends, stock indices S&P 500 and S&P/HKEC LC, and the inflation rates of the U.K. and China. The standardized beta-value 0.171 indicated that a unit increase in Google search trends would result in a 17.1% increase in Bitcoin price. Similarly, beta-values 0.582 and 0.337 suggested a unit increase in S&P 500 and S&P/HKEX LC values would result in a 58.2% and 33.7% increase in Bitcoin price, respectively. Concerning inflation rates, a unit increase in the U.K. inflation rate (beta-value=0.279) would result in a 27.9% increase in Bitcoin price, while a unit increase in China's Inflation rate (beta-value=0.083) would result in an 8.3% increase in Bitcoin price.

In contrast, statistically significant negative relationships were observed between the digital asset and Hong Kong's inflation rate, stock index Shanghai Composite and Oil prices. A unit increase in the Hong Kong inflation rate (beta-value=-0.062) would result in a 6.2% decrease in Bitcoin price, while a unit increase in the Shanghai Composite index (beta-value=-0.194) value would result in a 19.4% decrease in Bitcoin price. Regarding the relationship with Oil (beta-value=-0.136), a unit increase in the value of Oil would result in a decrease of 13.6% in Bitcoin's closing price.

As a result of the significant effect (relationships) implied, hypotheses H3, H4, and H5 were supported. Hypothesis H1 was partially supported due to the possibility of both positive and negative effects. Hypothesis H2 was not supported.

4.3.2 Ethereum

A total of 93 observations related to Ethereum were analyzed, resulting in evidence of statistically significant relationships between Ethereum closing price and stock indices KOSPI, S&P/HKEC LC and Shanghai Composite, Gold, Oil, the U.K. inflation rate, and Google search trends related to Ethereum. The adjusted R^2 value, 0.928, indicated that these variables could explain 92.8% of the variation in Ethereum closing price, while 7.2% could be because of variables not captured in this research.

Statistically significant positive relationships were suggested between Ethereum closing price and stock indices KOSPI and S&P/HKEX LC, Gold, U.K. inflation rates, and Google search trends related to Ethereum. KOSPI and S&P/HKEC LC have beta values of 0.283 and 0.515, respectively, indicating that a unit increase in the value of the indices would result in a 28.3% and 51.5% increase in Ethereum closing price, respectively. Gold and U.K. inflation rates had beta-values of 0.178 and 0.567, respectively, a unit increase in the two assets resulting in a 17.8% and 56.7% increase in the closing price of Ethereum. Regarding the effect from Google search trends, a unit increase in the trends was suggested to result in a 14.5% increase in the closing price.

On the other hand, a statistically significant negative relationship was indicated between Ethereum's closing price and the Shanghai Composite index, with a unit increase in Shanghai Composite's value resulting in a 28.6% decrease in Ethereum's closing price. Additionally, a negative relationship was observed between Oil and cryptocurrency, but due to a p-value greater than 0.05 was flagged as insignificant to this study.

In summary, based on the relationships observed for this cryptocurrency, hypotheses H1 was partially supported through the positive effect from KOSPI and S&P/HKEX LC, H2 was supported through the positive effect from Gold, H3 was not supported as the negative effect from Oil was not significant. H4 was supported through the positive effect from U.K. inflation rates, and H5 was supported through the positive effect from Google search trends related to Ethereum.

4.3.3 Tether

There were no significantly related variables in this study about Tether hence no regression was performed. From the initial stage of checking for correlations, there was no significant correlation between Tether and any of the selected variables.

The values related to Tether's closing price were re-examined to verify whether a method or data issue caused this anomaly. It led to a discovery that the closing prices for this digital asset demonstrated a notable tendency to hover near the $1 threshold. The implications of this will be discussed further in Discussion Section. However, it did not imply a complete lack of relationship between Tether and the independent variables selected for this research. However, it indicated the need to apply different analyses and sampling frequencies to discover/deny any connections between the cryptocurrency and the selected factors in future works.

4.3.4 Binance Coin

Although a statistically significant regression model was derived for the Binance coin, it failed to fulfill the homoscedasticity assumption. Therefore, it will not be discussed further to ensure credibility due to the violation of the assumption as heteroskedasticity leads to the exaggeration of beta values and over-fitting of the model. Considering this, in a similar fashion to Tether, none of the five hypotheses regarding Binance Coin demonstrated significant support. For valid inferences to be made, a different approach would need to be taken to analyze relationships about the Binance coin, as will be discussed in the following chapters.

4.3.5 USD Coin

Akin to the Binance coin, USD Coin violated the assumptions of normality and linearity, only adhering to homoscedasticity. The violation of these assumptions indicated that a non-linear or non-parametric approach may have been more appropriate to uncover any underlying relationships between USD Coin's closing prices and the variables selected for this research. Therefore, it results in all five hypotheses failing to be supported.

4.3.6 Ripple

A statistically significant relationship was observed between 111 observations of Ripple and stock indices S&P 500 and S&P/HKEC and U.K. inflation rates. All observed relationships were positive. The results summarized in Table 10 indicated that 83.1% (Adjusted R2=0.831) of the variation in Ripple's closing price could be explained by these variables implying the remaining 16.9% was a result of other variables not included in this model.

S&P 500 had a beta-value of 0.225, indicating that a unit increase in the value of the index would result in a 22.5% increase in Ripple's closing price. S&P/HKEX had a beta-value of 0.654, implying a unit increase in the stock index's value would result in a 65.4% increase in the closing price of Ripple. Additionally, a unit increase in U.K. inflation rates was suggested to result in a 45.3% increase in Ripple's closing price (Refer to Table 10).

The positive relationship between S&P 500 and S&P/HKEX LC supported H1, while the positive relationship to the U.K. inflation rates supported hypothesis H4. As no evidence was provided regarding H2, H3, and H5, the three were deemed unsupported in the context of this digital asset.

4.3.7 Cardano

Based on 67 monthly observations of Cardano closing price, a statistically significant regression result was obtained that implied the relationship between Cardano closing price and stock indices Shanghai Composite and SMI, U.S. inflation rates, and Google search trends related to Cardano. The model derived had an adjusted R2 of 0.826, indicating that the variables included could explain 82.6% of Cardano's closing price variations. It implied that the remaining 17.4% was due to factors not included in the final regression model.

According to the results presented in Table 11 (Refer to Table 11), a significant positive relationship was observed between Shanghai Composite, U.S. inflation rates, and Google search trends. In contrast, an insignificant negative effect was observed concerning the SMI stock index. CHN_Stock, U.S. inflation rates, and Google search trends had beta values of 0.335, 0.525, and 0.420, indicating a unit increase in each would result in 33.5%, 52.5%, and 42.0% increases on Cardano's closing price.

The digital asset positively affected from the stock index Shanghai Composite, U.S. inflation, and Google search trends supporting H1, H4, and H5. However, H2 and H3 were not supported; no significant relationship was observed between Gold and Oil.

4.3.8 Dogecoin

One hundred eleven observations related to Dogecoin were analyzed, resulting in a statistically significant relationship between Dogecoin closing prices and stock indices S&P 500 and KOSPI and U.K.'s inflation rate. The regression analysis resulted in an adjusted R2 of 0.937, indicating that 93.7% of the variations in Dogecoin's prices could be explained through these variables. It would imply that the remaining 6.3% was accounted for by factors not included in this analysis.

The regression results tabulated in Table 12 (Refer to Table 12) indicate that the relationships observed were all positive. S&P 500 and KOSPI values had beta values of 0.614 and 0.244, indicating that a unit increase in each would result in a 61.4% and 24.4% increase in Dogecoin's closing price. In comparison, a unit change in U.K. inflation rates would result in and 22.6% increase in the cryptocurrency's closing price.

As for hypothesis testing, the positive effect from S&P 500 and KOSPI provided evidence to support H1, while the positive effect from U.K. inflation rates supported H4. Due to a lack of evidence, Dogecoin deemed H2, H3, and H5 unsupported.

4.3.9 Solana

This analysis had the lowest number of observations (N=37). The regression analysis summarized in Table 13 resulted in a statistically significant relationship between Solana and Nikkei 225, Switzerland's inflation rate, and Google search trends related to cryptocurrency. The adjusted R2=0.911 indicated that the three variables could explain 91.1% of the price variations in Solana's closing price, while the outstanding 8.9% was factored by variables not included in this analysis.

All three variables indicated a positive effect on Solana. A unit increase in Nikkei 225 resulted in approximately a 45.9% increase in Solana closing prices. A unit increase in the inflation rates of Switzerland would result in a 17.5% increase in the closing price. In comparison, a unit increase in Google search trends related to the asset would result in a 51.8% increase in Solana's closing price (Refer to Table 13).

Evidence of positive relationships between Solana and the stock index Nikkei 225, the Switzerland inflation rate, and Google search trends related to the asset allowed H1, H4, and H5 to be supported as valid hypotheses, while H2 and H3 lacked evidence.

4.3.10 Polygon

The final analysis used 48 observations and implied a statistically significant relationship between Polygon closing prices and the KOSPI stock index, Oil, and U.S. inflation rates. The derived results presented in Table 14 suggested that the three could explain 91.2% of the variation in Polygon price. The 8.8% remainder would suggest the existence of influential factors not included in this study.

A significant positive effect was suggested between Polygon's closing prices, KOSPI, and the U.S. inflation rate. A unit increase in KOSPI value would result in a 39.2% increase in Polygon's price. Additionally, a unit increase in U.S. inflation rates would result in a 104.0% increase in the cryptocurrency's price.

In contrast, Polygon and Oil implied a significant negative relationship. A unit increase in oil price would result in a 33.4% decrease in Polygon's price (Refer to Table 14).

Based on the results, a positive relationship between the KOSPI index and U.S. inflation rates provided evidence to support H1 and H4. Moreover, the negative relationship with Oil deemed H3 a valid hypothesis. There was, however, no evidence of Polygon's relationship with Gold and Google search trends; hence H2 and H5 were not supported.

4.4 Hypothesis Testing

The results of the hypotheses tests were previously discussed concerning each cryptocurrency; hence, this section summarizes the findings in Table 8.

Table 8. Summary of Hypothesis Testing

Cryptocurrency	H_1	H_2	H_3	H_4	H_5
Bitcoin	*		√	√	√
Ethereum	*	√		√	√
Tether					
Binance Coin					
USD Coin					
Ripple	√			√	
Cardano	√			√	√
Dogecoin	√			√	
Solana	√			√	√
Polygon	√		√	√	

The (√) symbol indicates the hypothesis was supported, with the (*) indicates the hypothesis was partially supported. The unmarked cells portray the hypotheses that were not supported about each cryptocurrency.

5. DISCUSSION

This study aimed to verify whether a relationship existed between cryptocurrencies and stock market indices, Gold, Oil, inflation rates, and level of interest or buzz, which was proxied by Google search trend data. Furthermore, this research aimed to answer whether cryptocurrencies were influenced by the same factors and in the same way and identify whether certain countries or regions were more influential to the crypto market than others.

Cryptocurrency concerning the stock market: The first hypothesis, H1, investigated the existence of a positive relationship between cryptocurrency and stock markets and was supported in 5 cryptocurrencies (Ripple, Cardano, Dogecoin, Solana, and Polygon), partially supported in Ethereum and Bitcoin and unsupported in the case of Tether, Binance coin, and USD Coin.

Bitcoin, Ripple, and Dogecoin showed positive relationships with the S&P 500, suggesting evidence of these cryptocurrencies' reliance on the stock indices. The findings, especially in the context of Bitcoin, are in line with studies carried out by Uddin et al. (2022) and Nguyen (2022), who believed there were possibilities in the co-movement of Bitcoin and this stock index which would also imply that both faced a similar downward trend in the case of adverse market shocks.

The Hong Kong stock index S&P/HKEX LC was positively linked to Bitcoin, Ethereum, Ripple, and Cardano, further strengthening the notion of co-movements between stock markets and cryptocurrencies. Moreover, this observation is corroborated by Zeng and Ahmed (2022), who found a significant market integration and volatility spillover across East Asian Stock markets and Bitcoin. In their study, Hong Kong, China, Japan, and Korea had significant risk spillover to other markets, which put means events that affect stock markets in these countries, such as downturn, would have a ripple effect on other markets, in this case, the cryptocurrency market, hence the positive relationship observed.

Ethereum, Polygon, and Dogecoin also portrayed a positive relationship to the Korean representative stock index KOSPI. Based on the existing research, the inclusion of KOSPI in analyzing the interaction between stock markets and cryptocurrencies has been limited. However, since the trend was perceived across multiple currencies, an opportunity arises for exploring untapped market insights. KOSPI is regarded as one of Asia's most prominent and influential stock markets. Therefore this observation is regarded as more than a coincidence and warrants further exploration.

Evidence of the positive relationship between Bitcoin and the Nikkei 225 was found by Panagiotidis et al. (2018) through a LASSO approach. While this is not directly linked to Solana. This cryptocurrency showed a positive effect from the index; it suggests that the stock index is a significant indicator of the variations in cryptocurrency prices. Also, iterating on the previously discussed work by Zeng and Ahmed (2022), Asian markets portray the potential to cause a ripple effect on other markets, providing strength to this observation.

However, while mostly positive relationships were observed between cryptocurrencies and stock markets, a negative relationship was observed between the Chinese stock index Shanghai Composite and significant cryptocurrencies, Bitcoin and Ethereum. This observation is backed by Wang et al. (2019), who suggested that Bitcoin can be used as a hedging tool for stocks in China as an asymmetric relationship was evidenced between the two. Hedging refers to using an alternative asset to reduce the downside risk or potential losses related to another. Therefore, during adverse stock market shocks related to Shanghai Composite, investing in cryptocurrencies (Bitcoin and Ethereum) could offset the potential losses faced.

As most of the observations align with existing theories and studies, it is deemed that the evidence for the presence of the relationships discussed above is coherent and credible.

Cryptocurrency about Gold: The second hypothesis, H2, investigated the theory of the positive relationship between cryptocurrencies and Gold. This study only supported this relationship in the context of Ethereum. Previous studies (Beganski, 2023; Bouri et al., 2017; Aloui et al., 2021) indicate that Gold has been used to mitigate effects due to inflation, showing little or negative correlation to other traditional assets such as stocks and bonds, hence often referred to as a safe-haven asset for investors.

The positive relation between Ethereum and Gold is supported by Ghorbel and Jeribi (2021), who applied a BEKK-GARCH model to investigate volatility spillover between cryptocurrencies and other financial assets. Can Ethereum be considered a haven or a better investment option than Gold? Several studies have contradictory opinions; hence this provides an avenue for further research and could prove significant to stakeholders in both markets.

Cryptocurrency about Oil: In support of the H3, Bitcoin, and Polygon indicated negative relationships to Oil. The observation in terms of Bitcoin is contradicted by the previously discussed study by Ghorbel and Jeribi (2021). Their research shows that Ethereum was negatively correlated to WTI (World Texas Intermediate), the index related to Oil and used in this study. In contrast, Bitcoin showed a mostly positive relationship to the asset. Contrarily, Jareño et al. (2021) found a statistically negative correlation between Bitcoin and oil returns when analyzing the sensitivity of Bitcoin returns to international risk factors such as Gold, Oil, and stock markets.

Additionally, the notion that increasing oil prices could affect cryptocurrency mining and production exists. Since the process requires energy to execute, increasing oil prices would increase production costs, decreasing the cryptocurrency's output. It is reinforced by Salisu et al. (2023), who observed that higher oil prices led to the lowering of Bitcoin's returns and, by extension, its trading and volatility, implying a negative relationship between the two; hence the observation in this study is statistically sound.

Cryptocurrency price behavior about inflation: H4 was the most supported hypothesis in this study, portraying significant results in all seven cryptocurrencies that produced statistically significant regression results. The relationships were primarily positive, with the exemption of Hong Kong's inflation rate indicating a negative relationship with Bitcoin.

The positive correlations to the U.S., U.K., China, and Switzerland inflation rates imply that cryptocurrencies would play suitable hedging alternatives in these regions. In China especially, this is a sound observation as results previously related to the representative stock index Shanghai Composite indicated the same. To further break down the connection in concepts, stock markets are susceptible to changes in inflation rates in countries as a fiat currency largely backs them, i.e., government-issued money. Therefore, it implies that an increase in inflation rates would decrease stock market returns. In the case of the Shanghai Composite, the correlation was negative, suggesting that investing in cryptocurrency would be an excellent way to help reduce the losses during periods of downward trends in the stock market. It sums up the theory of cryptocurrencies playing a hedging tool for inflation rates.

Additionally, Nasreen et al. (2022), Conlon et al. (2021), and Sarker and Wang (2022) all agree that there is a positive relationship between cryptocurrencies and inflation rates of several countries, including the U.K. and U.S., evidenced in this study as well.

Cryptocurrency about Google search trends: H5 explored the positive effect relation between Google search trends and cryptocurrencies, supported by Bitcoin, Ethereum, Cardano, and Solana. While the study by Aslanidis et al. (2022) backs the influence of Google trends on Bitcoin's price, it is implied that information flows from the volatility of the cryptocurrency to Google search trends is more prominent, i.e., the variation in Bitcoin price result in more Google trend activities. Therefore, examining the evidenced bidirectional relationship would prove more fruitful in interpreting the results. Additionally, to comprehensively incorporate the influence of the level of interest in the form of buzz, analyzing internet blogs and web forums related to cryptocurrency would help map out any linkage between the two.

Discussion on research questions: Based on the results obtained in this research, stock markets and inflation rates highly affect cryptocurrencies, as all seven cryptocurrencies for which statistically sound results were obtained supported the hypotheses related to the two factors. It, therefore, feeds into the notion of co-movements between the stock market and the cryptocurrency market, as well as cryptocurrencies' viability to act as hedges for inflation due to high inflation rates attract more stakeholders to the market and reduce the risk of suffering total losses, which in turn affects cryptocurrency returns positively.

In terms of how each factor affected the cryptocurrencies, a similar direction in the relationships portrayed was seen across all relations, i.e., in the case of the S&P 500, which affected several cryptocurrencies, all the relationships indicated were in a positive light. Additionally, in the case of Oil, the relationship between Ethereum and Polygon was negative. In the case of this research, similar factors evidenced influence on cryptocurrencies in similar directions. However, some previous studies show a diversification of the impacts of similar factors on different cryptocurrencies; therefore, a discrepancy may have arisen due to differences in methods and frequency of data, i.e., weekly vs monthly observations.

The United States, United Kingdom, South Korea, Hong Kong, and China-related stock indices and inflation rates were evidenced to have more significant relationships with cryptocurrencies. While extensive study exists concerning the western region of the world (U.K. and U.S.), this study hinted at the potential spillover effects of Asian markets on cryptocurrencies, providing a new perspective on market indicators region-wise that can be explored further.

Lastly, based on the non-linearity evidenced by USD Coin, Tether, and Binance coin, it was implied that non-linear or non-parametric methods needed to be applied to further discover the influence of external market factors in this context. Hence this serves as one of the limitations of this research and a direction for future studies.

6. CONCLUSION

This study aimed to examine the potential correlation between cryptocurrencies and stock market indices, Gold, Oil, inflation rates, and the level of interest or buzz. Furthermore, this research aimed to address questions regarding the influence of these factors on cryptocurrencies, exploring if they affect cryptocurrencies similarly. Additionally, it sought to identify any notable disparities in the influence of certain countries or regions on the cryptocurrency market.

The findings in this research were able to verify and back observations made in previous works related to factors influencing cryptocurrency prices. Moreover, incorporating a more extensive array of cryptocurrencies compared to most of the research reviewed for this study, a new insight could be obtained for lesser studied cryptocurrencies like Cardano, Solana, and Polygon.

Additionally, an under-researched area was uncovered due to the indication of relationships between the cryptocurrencies and factors related to Asian markets, specifically South Korea, Hong Kong, and China. Moreover, the stance on cryptocurrencies acting as a hedging tool against inflation, hypothesized by many researchers and market experts, was supported further in this study.

This study applied a log-linear relationship between cryptocurrency closing prices and the predictor variables to assess their linear relationships in line with the study's objective. Additionally, this study should have highlighted the interconnectedness of the independent variables. Therefore, to assess and account for confounding factors not captured in the study due to this approach, the analysis can be converted to a time-series analysis to examine the effect of the variables in periods such as before or after market shocks or geopolitical events such as before and after the pandemic (Ampountolas, 2023). It will also provide a helpful avenue for price forecasting, which was outside the scope of this paper. Furthermore, examining cryptocurrency behavior in African markets is a recommendation for future works.

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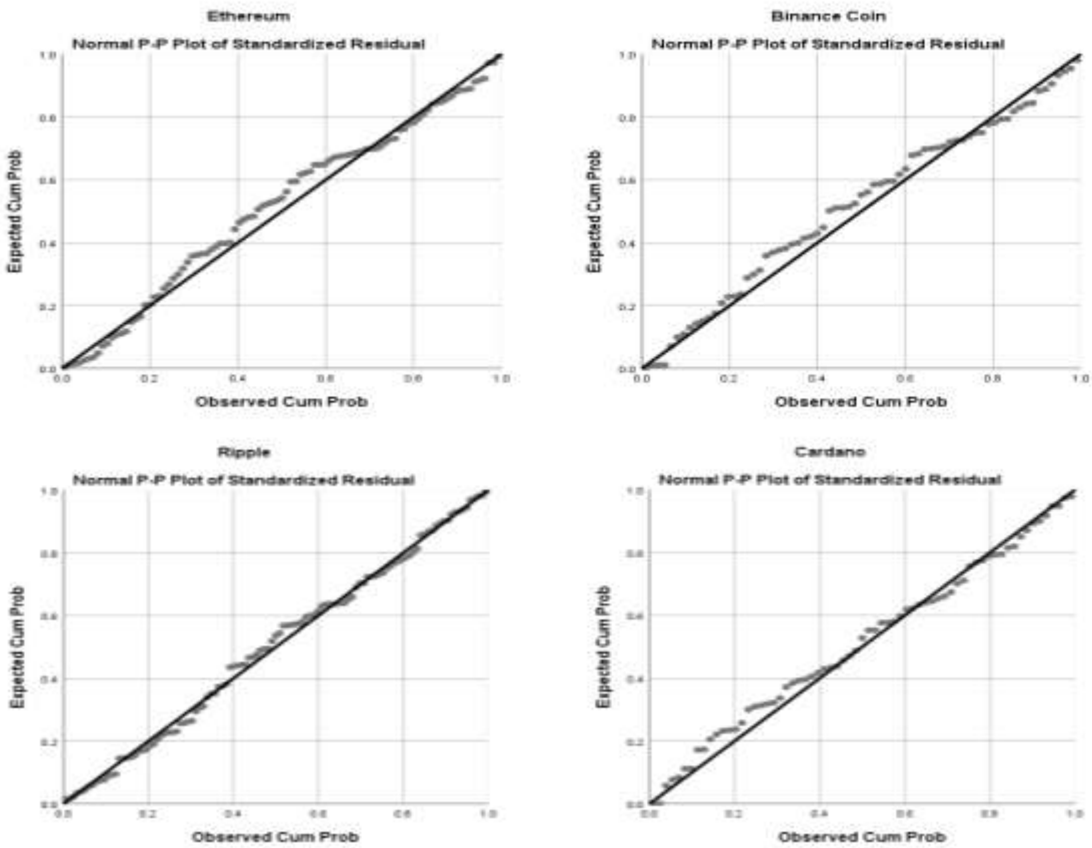
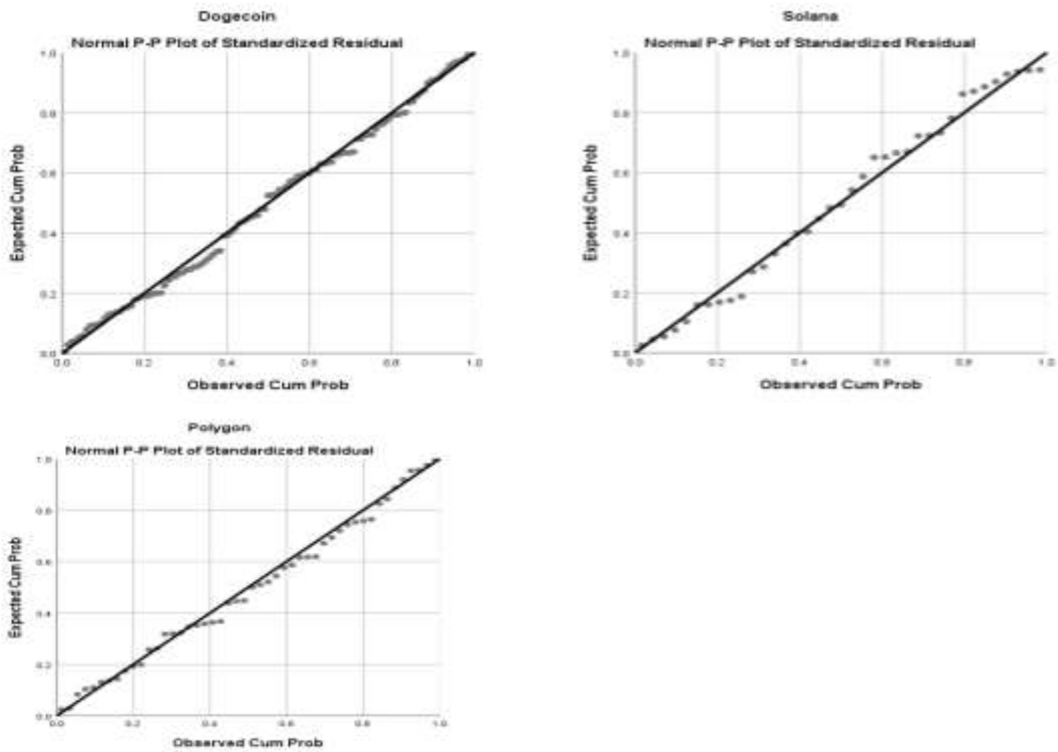
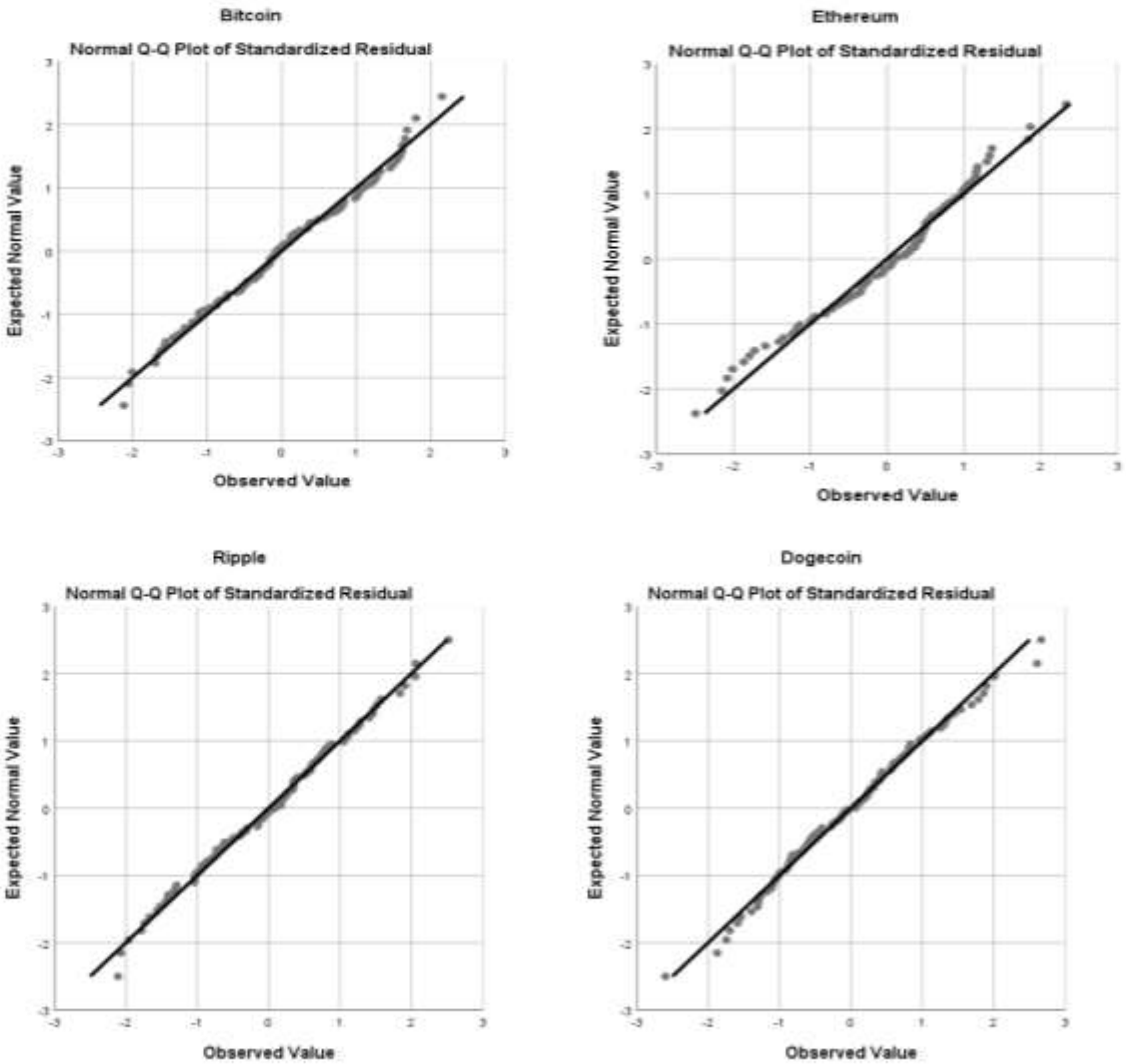
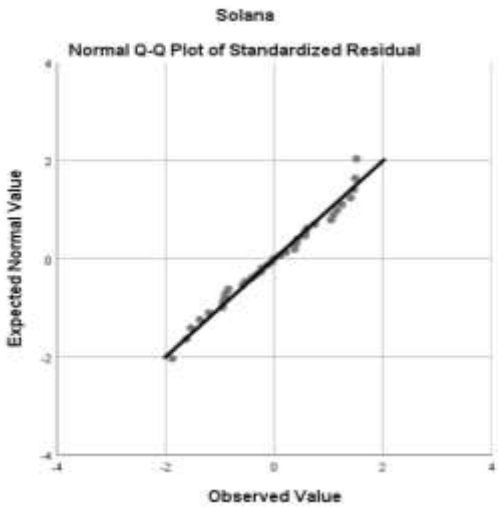
Appendix I

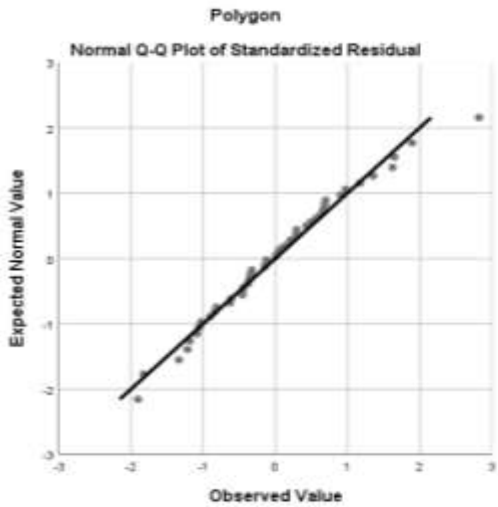




Appendix II. Normality Q-Q Plots of Residuals




Solana
Normal Q-Q Plot of Standardized Residual
Expected Normal Value
Observed Value


Polygon
Normal Q-Q Plot of Standardized Residual
Expected Normal Value
Observed Value