National College of Ireland

# Analytical Review of Cryptocurrency Dynamics in Geopolitical Conflicts: A Case Study of the Ukraine-Russia Conflict

MSc Research Project

Msc Fintech

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**National College of Ireland**

**MSc Project Submission Sheet**

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| **Module:** | MSc Research Project |
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| **Submission Due Date:** | 12th of August 2023 |
| **Project Title:** | Analytical Review of Cryptocurrency Dynamics in Geopolitical Conflicts: A Case Study of the Ukraine-Russia Conflict |
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**Analytical Review of Cryptocurrency Dynamics in Geopolitical Conflicts: A Case Study of the Ukraine-Russia Conflict**


## Abstract

This study exploring the Effect of Geopolitical Tensions Especially Russia-Ukraine Conflict On Cryptocurrency Market had three specific objectives of the study are: Examine geopolitical tensions and systemic risk in cryptocurrencies bidirectionally; Analyse inflation within Russia & Ukraine by investigating whether this conflict generated a demand for cryptocurrencies due to being an alternative method to hedge against adverse currency movements; Analyse the impact of changes in stock market indices in Russia and Ukraine on cryptocurrency market volatility during the war. Using the Capital Asset Pricing Model (CAPM) and correlation analysis, it investigate how these selected cryptocurrencies interact with traditional financial assets as crude oil prices or stock market indices; Results suggest that the significant role of market returns to cryptocurrency return was also affected by geopolitical shocks and hence rendering them as stable hedging instruments in times of global events. In addition to that a significant positive average relation between inflation rates and cryptocurrency prices especially in Russia is observed underlining the hedging capability of cryptocurrencies against inflation. With this in mind, the results of the research indicate that future studies aiming to capture more comprehensively cryptocurrency dynamics within geopolitical conflicts clouds must have access to broader datasets and deploy models with a better description power. These results offer critical information for investors, policymakers and researchers in cryptocurrencies including global macroeconomic markets.



**Keywords:** *Geopolitical tensions, Russia-Ukraine conflict, Cryptocurrencies, Capital Asset Pricing Model (CAPM), Systematic risk, Inflation, Hedging, Market volatility.*

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## 1.0 Introduction

Cryptocurrencies and digital tokens represent a new asset class that has shaken up the global financial landscape with an innovative way of transferring and storing value (Kayani & Hasan, 2024). The seed of this idea —coin— to create a decentralized cryptocurrency that is not tied in any way by the finances or debts produced and imposed from above, has been germinated now into something many business owners will be harvesting across globally (Rodeck, 2021). Smales (2019) noted that more apparent is the mounting bid for cryptocurrencies as a safe haven play amid economic and geopolitical instability. This study a case of the Ukraine-Russia conflict to analyze cryptocurrency markets dynamics with respect to geopolitical conflicts.

The conflict escalated in 2022, which has been one of the biggest catalysts for changes geopolitically as well in how financial markets have evolved over time (Izzeldin *et al*., 2023). According to Ullah *et al*. (2023), the conflict resulted in spurting a series of harsh economic sanctions on Russia that tampered with its central bank and disrupted capital markets leading to wild moves across the traditional financial ecosystem. This was the same logic that gave rise to cryptocurrencies as an emerging financial safe haven — a place where investors can store their money when markets start tumbling. (Conlon *et al*., 2020). This paper focuses on the impact of non-economic risks such as political tensions, war-sanction sentiment and a real economy channel (inflation & stock market index) over cryptocurrency markets during turmoil.

This study is conducted to further interpret how geopolitical activities correspond with developments and problems in cryptocurrencies. There are studies over so many years on how traditional financial assets react to historical geopolitical tensions — the narrative is known that while stocks and bonds get a whole lot worse in terms of volatility with an increase in risk aversion (Catalán *et al*., 2023). For investors and

policymakers, it is important to understand these dynamics in order to make informed investment decisions and develop regulatory frameworks (Rodrigues *et al*., 2024).

This study is guided by the primary research question: How geopolitical tensions, war-sanction-related sentiments, and macroeconomic variables, such as inflation and stock indices may affect the volatility and demand for Cryptocurrencies during the Ukraine-Russia conflict? To address this question, the study is structured around three key objectives;

- To investigate the bidirectional relationships between geopolitical tensions, war-sanction-related sentiments, and the systematic risks of cryptocurrencies during the Russia-Ukraine war.
- To examine how inflation in Russia and Ukraine influenced the demand for cryptocurrencies as a hedge against currency devaluation during the geopolitical tensions at the start of the Russian-Ukraine War.
- To analyse the impact of changes in stock market indices in Russia and Ukraine on cryptocurrency market volatility during the war.

This research contributes to the existing body of knowledge by providing empirical evidence on the interaction between geopolitical factors and cryptocurrency markets. By focusing on the Russia-Ukraine conflict, this study offers a case-specific analysis that highlights the unique challenges and opportunities presented by cryptocurrencies in times of geopolitical instability. This research has academic and practical significance in finance and international relations. The rest of this research is structured as follows: chapter two provides a literature review that contains both theoretical frameworks and empirical studies on geopolitical events hitting financial markets, with a specific nuance into cryptocurrencies. Chapter three discusses the research methodology: the data sources used, analytical tools employed and how they underpin the empirical framework to address the research questions. The design specifications are presented in chapter four, chapter five then discusses the proposed solution (implementation), then the chapter six then discusses the analysis of the results and main findings. Chapter seven concludes the study and gives a summary of key insights along with directions for further research.

## 2.0 Related Work

### 2.1 Introduction

The Literature Review emphasises a critical look at the research already conducted in relation to interactions of geopolitics, macroeconomic variables and cryptocurrencies. A good understanding of these dynamics is crucial to know how these forces affect cryptocurrency markets, especially with scenarios like the Ukraine-Russia conflict. This review provides a discussion of key theoretical frameworks and empirical studies to give a background needed for this research. The chapter is structured into several sub-sections: the theoretical underpinnings of systematic risk and geopolitical risk, the impact of geopolitical tensions on financial markets, and the role of macroeconomic variables such as inflation, interest rates, and stock market indices on cryptocurrency dynamics.

### 2.2 Theoretical Frameworks

Theoretical frameworks serve as a basis for understanding systemic and geopolitical risks in financial markets (Zaremba *et al*., 2022). These are the frameworks needed to study how cryptocurrencies can behave in the Ukraine-Russia conflict. For instance, detailed versions of the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) are presented, along with certain takes on understanding geopolitical risk questions, as well as cryptocurrencies' role in hedging.

#### 2.2.1 Systematic Risk in Financial Markets

***Capital Asset Pricing Model (CAPM)***

The Capital Asset Pricing Model (CAPM) is a staple of financial theory, which originally measured systematic risk or market risk that cannot be mitigated through diversification, either across industries and sectors or between long-term investments (Kenton, 2023). According to capital asset pricing model, an assets expected return is directly proportional to the beta of that security's sensitivity to market movements (Chen, 2021). This relation can be written as:

$$\mathbf{E(R_i) = R_f + \beta_i\,(E(R_m) - R_f)}$$

where $E(R_i)$is the expected return on the asset,

$R_f$ is the risk-free rate,

$\beta_i$ is the beta of the asset, and

$E(R_m)$ is the expected return of the market.

The CAPM model assumes that investors are rational, and markets are efficient, which leads to the consideration of only systematic (or market) risk in the pricing of assets (Chen, 2021). Yet the model is also criticized for its restrictions which include assuming only one risk factor (market risk) and applying it to exotic assets such as cryptocurrencies (Kenton, 2023).

### *Arbitrage Pricing Theory (APT)*

To address the limitations of CAPM, Stephen Ross created Arbitrage Pricing Theory (APT) in 1976 which considers multiple factors that might affect the return on an asset (Nickolas, 2019). The factors with APT are not defined, but systematic risks like macro-economic or geo-political risk could be some of the other variables considered (Hayes, 2020). The APT model is expressed as:

$$\mathbf{E(R_i) = R_f + \sum_{j=1}^{n} \beta ij Fj}$$

where $\beta_{ij}$ *represents the sensitivity of the asset to the* $j^{th}$ *factor* $F_j$.

This is especially appropriate for the present study given that APT provides a theoretical foundation to explore how different macroeconomic and geopolitical determinants jointly affect cryptocurrency returns (Hayes, 2020). Due to this flexibility, APT is able to provide a more in-depth analysis than CAPM could ever be when discussing about novel assets like Cryptocurrencies (Conscentia Beam, 2024).

### *Relevance to Cryptocurrencies*

Since then, the principles of CAPM and APT have been hotly debated in papers on cryptocurrency (Conscentia Beam, 2024). According to Bennett et al. (2023), since cryptocurrencies are decentralized and have no basic value drivers, such as earnings or dividends, these assets do not always lend themselves to

traditional models of asset pricing. The empirical results are mixed, with some studies finding that cryptocurrency returns cannot be explained by CAPM alone and hence other factors including investor sentiment or technological innovation may be influencing their risk-return characteristics (Seabe *et al*., 2024). By contrast, Yadav and Hegde (2022) noted that APT's multifactor model has been better able to grasp cryptocurrency market dynamics even when factoring in characteristics such as liquidity levels or shifts in regulation and political climate. APT is more versatile than CAPM and is a better model to capture the systematic risk of cryptocurrencies, especially during uncertain periods like the Ukraine-Russia conflict (Ullah *et al*., 2023).

### 2.2.2 Geopolitical Risk and Financial Markets

The geopolitical risk related to political instability, war, or policy changes can affect financial markets (Ma *et al*., 2024). Adrian (2021) stated that an element which has become more critical in the world of global finance as political events can result in overnight shifts to markets and by default advance or reduce investor confidence moving asset prices. One of the most common of such indices is called the Geopolitical Risk Index (GPR) (Yang *et al*., 2021). The GPR index reflects the geopolitical landscape and its effects in relation to capital markets (Kaartinen, 2023). Such index-like measures, including this one and others of a related nature, have been applied to analyse the impact on different types of asset classes, providing a quantified way for understanding these risks (Gabriel *et al*., 2024).

Geopolitical risks are well understood in the context of traditional financial assets such as stocks, bonds, and commodities (NguyenHuu and Deniz, 2023). For example, wars, terrorist attacks or countries with sustained political instability can hike stock market volatility, lead to a flight of investment towards safe-haven assets like gold, and disrupt commodity prices (IMF, 2023). Jung *et al*. (2021) noted that, normally, investors react to geopolitical risks by changing their portfolio exposures — predominantly cutting riskier assets and taking more of an in-and-out approach with safer ones. This has been seen in various forms, including the Gulf Wars and most recently with Brexit voting. The response of traditional assets to

geopolitical risks provides a benchmark for understanding how newer assets, like cryptocurrencies, might behave under similar circumstances (Holovatiuk, 2024).

After all, applying geopolitical risk analysis to cryptocurrencies is a rather recent field of research. One of the most common ways cryptocurrencies are marketed is as decentralised, so in theory they should be immune from government censorship and thus less susceptible to geopolitical risks than conventional assets (Schar & Berentsen, 2020; Owen, 2015). Nevertheless, empirical studies (Rodrigues *et al*. 2024; Nidhal-Mgadmi *et al*., 2023) show that cryptocurrencies issuance are not immune to the current geopolitical debacles. As noted by Rodrigues *et al*. (2024), there has been evidence that geopolitical tensions, especially between economic powerhouses have had an effect on the pricing and volatility of cryptocurrencies. For example, both Bitcoin and Ethereum saw high price volatility as tensions increased in the Ukraine-Russia conflict (Nidhal-Mgadmi *et al*., 2023). The unique position of cryptocurrencies as both speculative assets and potential safe havens makes their response to geopolitical risks complex and multifaceted, requiring further investigation (Iyer and Popescu, 2023).

### 2.2.3 Theories on Cryptocurrency as a Hedge

#### *Safe-Haven and Hedge Properties*

During times of economic uncertainty and acute geopolitical instability, notions as to cryptocurrencies being harbours or hedges that are immune to these effects have been gaining popularity (Rodrigues *et al*., 2024). A safe-haven type asset is one that does not lose value or increases when all the other assets are losing. Regarded as a hedge in finance parlance, it will typically offset the risk of another specific risky investment (Chen, 2023). Kliber *et al*. (2019) noted that Bitcoin in particular has been analysed deeply as a potential safe-haven or hedge, with mixed results. Chemkha *et al*. (2021) explained that while some research shows Bitcoin serves as a diversification tool for traditional assets in the presence of increased market uncertainty, other work such as Vo, Chapman & Lee (2022) reports that its high volatility detracts from its hedging properties and thus impedes it from functioning effectively as a safe haven.

#### *Empirical Evidence*

On the other hand, empirical research has delivered mixed findings on whether cryptocurrencies serve as hedges or safe-haven assets (Rashid *et al*., 2022). According to Phochanachan *et al*. (2022), this includes a class of military research indicating that Bitcoin can be used to hedge against inflation and devaluation, becoming an attractive asset in countries experiencing economic instability such as the recent Ukraine-Russia conflict. However, other studies have found some evidence of a safe haven role for cryptocurrencies during financial crises, depending on market conditions and investor sentiment (Conlon *et al*., 2020). Samuele (2024) noted that cryptocurrencies were also used as a safer asset for preserving its value in countries whose fiat currency was being undermined during the conflict. However, the extreme volatility and speculative traits of cryptocurrencies imply that unlike traditional assets, their safe-haven or hedging function is not stable, but instead substantially varies across different geopolitical and economic conditions (Zhang *et al*., 2023).

## 2.3 Geopolitical Tensions and Cryptocurrency Markets

### 2.3.1 Impact of Geopolitical Tensions on Financial Markets

Global financial markets are affected every time geopolitical tensions reach a fever pitch (IMF, 2023). Key studies suggest that, in order to mitigate their risks, investors often reallocate from riskier assets into safe havens during certain times of socio-political unrest or tension, which are normal triggers for high market volatility — such as military conflicts or political instability (Ma *et al*., 2024). For example, the recent Gulf Wars and Brexit referendum led to large fluctuations in global stock markets and commodity prices, indicating few political risks that could rock traditional financial institutions (Ma *et al*., 2024). For instance, the Ukraine-Russia war presented a glaring example of how geo-political tensions can rattle financial markets with stock indices becoming more volatile and currencies being devalued partially, as well as commodity prices especially in energy market moving down (Manelli *et al*., 2024).

### 2.3.2 War-Sanction-Related Sentiments and Cryptocurrency Dynamics

Economic sanctions are regularly used as a geopolitical strategy and they have deep financial market impacts, which also affect cryptocurrencies (Rodrigues *et al*., 2024). According to O'driscoll (2017), sanctions not only serve to isolate the economy of a nation, but they can also lead to skyrocketing capital flight and devaluation. With the ongoing conflict happening in Russia and Ukraine that had notable ramifications when sanctions were placed on Russians — this has caused a monetary behaviour shift or revolution, where institutional investors and the retail sector have sought refuge in cryptocurrencies to escape from traditional financial systems (Ullah *et al*., 2023). Research by Siripurapu and Berman (2024) shows that war-sanction-induced feelings influenced the supply, price, and volatility of cryptocurrencies, as investors traded in defiance to scrutinies by governmental bodies. They approached cryptocurrencies for need of protection against monetary devaluation or simply preservation of wealth due to a quickly collapsing economic space.

### 2.3.3 Bidirectional Relationships

Previous empirical literature has mostly focused on capturing the dynamics between geopolitical instability and cryptocurrency markets, either through linear correlations or by employing Granger causality tests to determine whether there are causal linkages among these variables (Köse and Ünal, 2023). Such studies illustrate not only the importance of geopolitical risks on cryptocurrency performance and realized volatility–also that cryptocurrency dynamics might reflect and externally boost such type of geo-political sentiments (Rodrigues *et al*., 2024). However, gaps remain in the literature, particularly regarding the long-term effects of such tensions on cryptocurrency markets and the potential for cryptocurrencies to serve as early indicators of geopolitical instability. Further research is needed to fully understand these complex interactions.

## 2.4 Identification of Gaps in the Literature

Despite extensive research on the intersection of geopolitical tensions and financial markets, several questions remain inadequately addressed, particularly concerning the nuanced behaviour of

cryptocurrencies (Catalán *et al*., 2023). There is a lack of comprehensive models that integrate multiple macroeconomic variables—such as inflation, interest rates, and stock indices—with geopolitical factors to fully capture their combined effects on cryptocurrency dynamics. Specifically, in the context of the Ukraine-Russia conflict, the literature has yet to thoroughly explore the long-term impacts of war-sanction-related sentiments on cryptocurrency volatility, as well as the bidirectional relationships between geopolitical events and market responses.

## 3.0 Research Methodology

This chapter describes the research methodology with details on how data was collected, which analytical techniques and valuation methods deployed to study the influence of geopolitical tensions and macroeconomic variables in cryptocurrency markets during Russia — Ukraine conflict. The approach is both designed to create a robust and methodologically sound way of assessing relationships between the key variables identified in the search.

### 3.1 Data Collection

The source of the data for this study was from dependable and internationally renowned financial databases, to ensure correctness and credibility (Simera *et al.*, 2010). Yahoo Finance or World Bank website and Investing.com, respectively were the main sources of data for this research. Specifically, cryptocurrency data for BTC, Ethereum, Solana, Litecoin, Dash, Ripple, DigiByte and XEM, as well as S&P 500 index data was gathered from Yahoo Finance with help of the yfinance Python library. Despite BTC and Ethereum being the most popular by ranking by market capitalization, reflecting their dominance in the market and more prominent de-facto use during the geopolitical war justified they deserve to be emulated by other cryptocurrency assets (Dagher *et al.*, 2024).

| *S/No* | *Cryptocurrency* | *Symbol* |
|---|---|---|
| *1* | *Bitcoin* | *BTC* |
| *2* | *Ethereum* | *ETH* |
| *3* | *Solana* | *SOL* |
| *4* | *Litecoin* | *LTC* |
| *5* | *Dash* | *DASH* |
| *6* | *Ripple* | *XRP* |
| *7* | *DigiByte* | *DGB* |
| *8* | *XEM* | *XEM* |

Inflation data about Ukraine taken from Worldbank, and inflation rates in Russia were found on Investing.com (Erlam, 2024). It provided the Consumer Price Index (CPI) monthly which, was used to forecast and compute inflation rates in India as well as USA (Krishnan, Moya and Halley, 2024). These sources were chosen due to their being considered comprehensive of relevant international economic indicators and having a regularity in the supply of data.

### 3.2 Data Collection Method

Data collection process had more than one step for capturing all the right variables. The yfinance package in Python was used to download cryptocurrency prices and the S&P 500 index data, which makes it easy to get historical price data with exact time frames (Shah, 2020). The data was further pre-processed to make everything consistent and needed measures were taken so that outliers, missing values could not give biased results (Kwak and Kim, 2017).

Inflation data was sourced from the World Bank and Investing. com websites (Erlam, 2024; World Bank, 2024). The monthly CPI values were input in Excel to compute the inflation rates for Russia and Ukraine every month. The data is important because it can give us an idea of the macroeconomic landscape during the conflict, which would be a strong indicator for potential demand or price effect on crypto due to competition.

### 3.2 Traditional Asset

The S&P 500 index was chosen as the traditional financial asset for comparison in this study. The S&P 500 is a stock market index that represents the performance of around five hundred mega-cap companies in America (Villalta, 2012). It is one of the most followed equity indices and many consider it to be a gauge of the U.S. stock market because financial companies have bigger weightings than technology firms in offering a true reflection of what people are willing to spend (Brzenk, 2018). The study selected the seven most popular stock market indices NASDAQ, SP 500, DAX, CAC 40, Nikkei, TSX and MOEX.

| *S/No* | *Market Index* | *Symbol* |
|---|---|---|
| *1* | *NASDAQ* | *^IXIC* |
| *2* | *SP 500* | *^GSPC* |
| *3* | *DAX* | *^GDAXI* |
| *4* | *CAC 40* | *^FCHI* |
| *5* | *Nikkei* | *^N225* |
| *6* | *TSX* | *^GSPTSE* |
| *7* | *MOEX* | *IMOEX.ME* |

### 3.3 Duration and Key Dates

In the study two different time frames were also stratified. A 413 days' time period considered during the Capital Asset Pricing Model for the Feb 24, 2022, to April 12, 2023 while a 24-month time period was used for correlation and regression analysis of Inflation rates and cryptocurrency is January 01, 2022 to January 01, 2024. This long-time frame enabled an in-depth examination of the longer term affects from conflict.

The Russia-Ukraine war was highlighted as a major event with potential cryptocurrency market impact with certain key dates. There are about 4 notable key dates within the Russian-Ukraine war stated below. Of the four, Feb 24, 2022, seems to have the most impact on inflation rate changes and cryptocurrency prices, so it was considered as the date for the shock variable. A shock window of 10days was selected.

1. February 24, 2022: Russian Invasion of Ukraine
2. February 26, 2022: SWIFT Sanctions Announced
3. March 8, 2022: U.S. Ban on Russian Oil Imports
4. March 23, 2022: Russia Demands Gas Payments in Rubles

## 4.0 Design Specification

### 4.1 Analytical Framework

An integrated analytical framework — combining different statistical and econometric techniques is employed in this paper to determine the relationship between geopolitical events, and macroeconomic variables change with cryptocurrencies markets. Basic elements of the framework are Capital Asset Pricing Model (CAPM), correlation and regression analysis.

### 4.1.1 Capital Asset Pricing Model (CAPM)

CAPM is the main model that measures the systematic risk of cryptocurrencies in relation to traditional assets such as S&P 500 index. This model is used to determine the expected return of an asset, based on its beta — in other words how much that particular stock bends when market moves were made. Using CAPM, this paper checked whether BTC, Ethereum, Solana, Litecoin, Dash, Ripple, DigiByte and XEM display any relationship between their returns over market risk in general during important worldwide geopolitical events. The model uses historical price data to calculate the expected returns and a risk-free rate (mostly based on U.S. Treasury yields) as well.

The following is the model;

$$\mathbf{E(R_i) = R_f + \beta_i\,(E(R_m) - R_f)}$$

where $E(R_i)$is the expected return on the asset,

$R_f$ is the risk-free rate,

$\beta_i$ is the beta of the asset, and

$E(R_m)$ is the expected return of the market.

### 4.1.2 Correlation and Regression Analysis

These macroeconomic variables include among other things the inflation rates in Russia and Ukraine, while this study uses correlation analysis as well as regression analysis to look into how far these two countries can influence cryptocurrency prices. The strength of the linear relationship between these variables is calculated using Pearson correlation coefficient. Finally, a set of multiple linear regression models are used to investigate the impacts together of inflation rates, stock market indices and geopolitical events on cryptocurrency returns and volatility. This method allows finding the most informative factors influencing on conflict period cryptocurrency market behaviour.

### 4.2 Implementation Tools

Python — A versatile programming language used frequently in financial analysis and the foundation for running the model analysis (Nelli, 2015). Python libraries like yfinance, pandas, statsmodels and arch are used to download data in python and perform statistical analyses and econometrics models (Pik and Ghosh, 2021). In Excel, calculated inflation from the original CPI dataset in a pre-process stage. The use of these tools guarantees the analysis to be efficient and reproducible, permitting a systematic exploration for answering our research questions in detail.

### 4.3 Model Functionality and Requirements

The models used in this study need a set of input data, including price historical prices for Cryptos and S&P 500, Inflation rates as well as dates related to geopolitical events. The models are process-oriented, and the functionality is designed so that everything can be iterated on as new times periods or assets emerge along with different key macroeconomic variables. Such flexibility is important to be able to model movements in the notoriously highly volatile cryptocurrency markets, particularly reflecting recent geopolitical changes following Russia's invasion of Ukraine.

## 5.0 Implementation

During the Russia-Ukraine crisis, this study reveals that macroeconomic variables and cryptocurrency markets can help us to evaluate a relationship between geopolitical tensions which were tested in this research using analytical models over an implementation phase. The code is implemented in Python on the Google Colab which makes use of key libraries like yfinance, pandas, statsmodels and arch to achieve data extraction, processing and analysis. This is the last part of the implementation outlining formatted code for models, data transformation methods and output produced.

The first step in the data collection was scraping cryptocurrency prices (and a few traditional market indices) from Yahoo Finance. To collect this, I used yfinance library so it is really simple task. Inflation rates for Russia and Ukraine are sourced from the World Bank, Investing. com, respectively. Data which has been

fetched from different cryptocurrency price fetching API's like Bitcoin (BTC), Ethereum (ETH), Solana (SOL), Litecoin (LTC,) Dash (DASH) Ripple (XRP) DigiByte (DGB') and XEM along with some traditional financial assets, available in daily & monthly frequency i.e. S&P 500, NASDAQ, DAX, CAC 40, Nikkei TSX & MOEX indices as well.

The data were pre-processed to remove classification errors, outliers and deal with missing values so that our dataset was cleaned for further analysis. The study used excel for tabulating the data of inflation and calculate monthly Inflation ratios then imported it back in python to do some coherence and regression analysis.

The model was tested over 413 days during which pivotal geopolitical events took place. The model treats (traditional) market returns as independent variables, and the return on cryptocurrency markets as a dependent variable. Furthermore, a dummy variable was used to account for market risk and returns during the Russian invasion of Ukrainian conflict.

The monthly inflation rate is given by the formula;

$$Monthly\ Inflation\ Rate = \left(\frac{CPI_{current\ month} - CPI_{previous\ month}}{CPI_{previous\ month}}\right) \times 100\%$$

Where,

$CPI_{current\ month} = The\ Consumer\ Price\ Index\ in\ the\ current\ month$

$CPI_{previous\ month} = The\ Consumer\ Price\ Index\ in\ the\ previous\ month$

In terms of correlation and regression, the research calculated monthly inflation rates with CPI data, and then checked how that affected the price of cryptos to observe if there was any level of correlation and confidence behind this connection between them. Individual regression models were created with each country´s inflation data in order to determine the relationship between this variable and future

cryptocurrency returns. The implementation provides us with results such as regression coefficients, R-squared value and correlation patterns which inform about the relationships among the variables.

## 6.0 Evaluation

### 6.1 CAPM Analysis of Cryptocurrency and Market Returns

The research used the Capital Asset Pricing model (CAPM) as our first experiment to evaluate this relationship between returns of chosen cryptocurrencies and traditional market indices (i.e., apply a shock variable representing Russian invasion in Ukraine). Results further suggest that the impact of shock variable on cryptocurrency returns remains insignificant across most market indices. Instead, the returns on regular assets like the S&P 500, NASDAQ and TSX were more correlated with cryptocurrency returns particularly BTC / ETH as shown in figures 1 and 2.

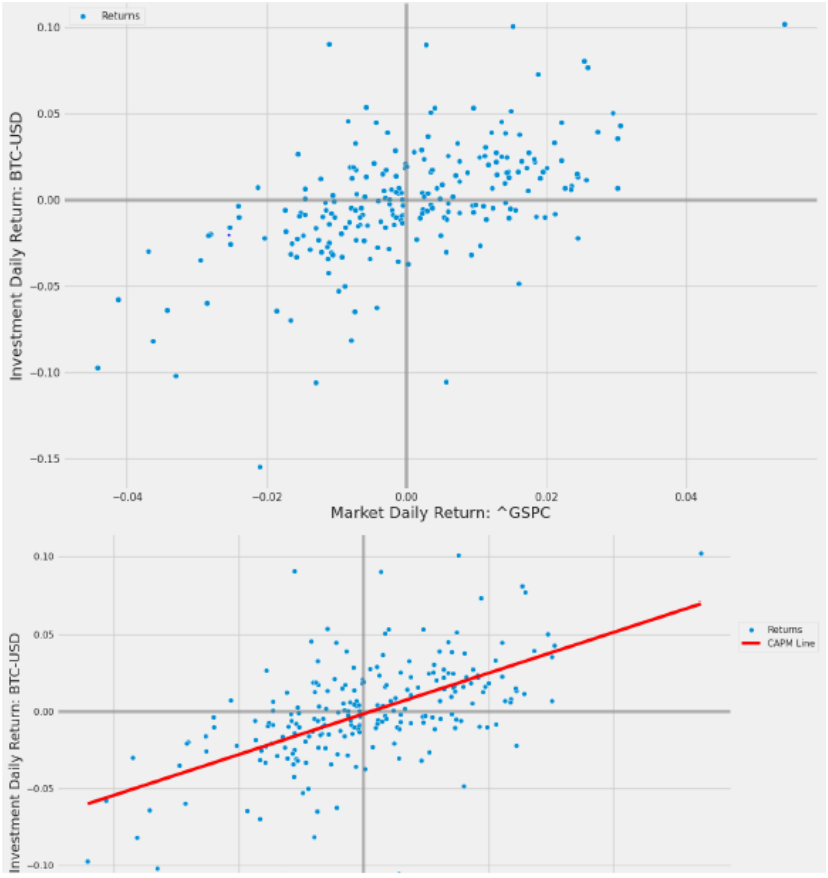

Figure 1: Plot of market vs investment returns from CAPM for BTC-USD using S&P500 market index.

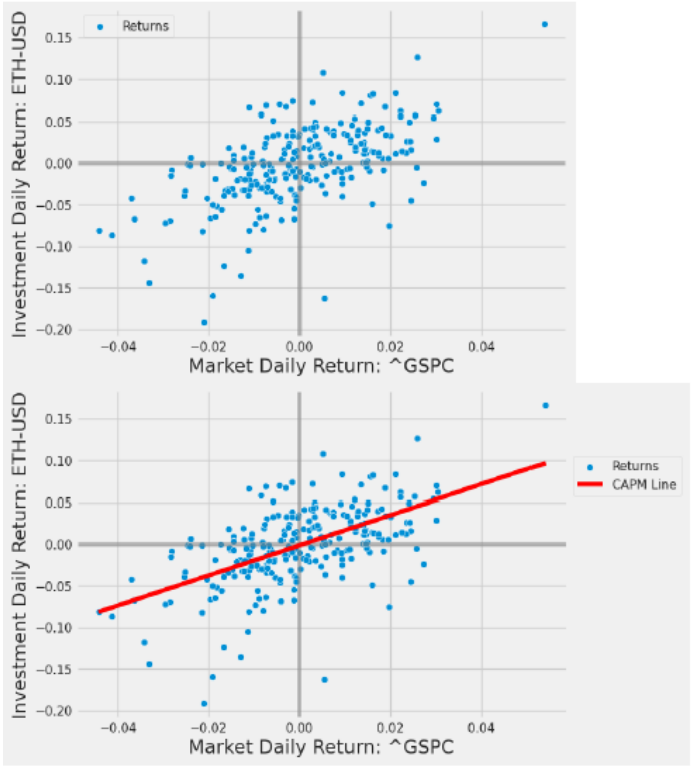


**Figure 2**: Plot of market vs investment returns from CAPM for ETH-USD using S&P500 market index

| **Cryptocurrency** | **Market Index** | **$R^2$** | **Significant Coefficient (Market Return/ Shock)** |
|---|---|---|---|
| **BTC-USD** | S&P 500 | 0.333 | Market Return (+) |
| **ETH-USD** | S&P 500 | 0.330 | Market Return (+) |
| **SOL-USD** | S&P 500 | 0.238 | Market Return (+) |
| **LTC-USD** | S&P 500 | 0.254 | Market Return (+) |
| **DASH-USD** | S&P 500 | 0.214 | Market Return (+) |
| **XRP-USD** | S&P 500 | 0.211 | Market Return (+) |

| | | | |
|---|---|---|---|
| **BTC-USD** | NASDAQ | 0.364 | Market Return (+) |
| **ETH-USD** | NASDAQ | 0.353 | Market Return (+) |
| **SOL-USD** | NASDAQ | 0.258 | Market Return (+) |
| **LTC-USD** | NASDAQ | 0.284 | Market Return (+) |
| **BTC-USD** | DAX | 0.092 | Market Return (+) |
| **ETH-USD** | DAX | 0.093 | Market Return (+) |
| **BTC-USD** | CAC 40 | 0.098 | Market Return (+) |
| **ETH-USD** | CAC 40 | 0.104 | Market Return (+) |
| **BTC-USD** | TSX | 0.260 | Market Return (+) |
| **ETH-USD** | TSX | 0.249 | Market Return (+) |
| **BTC-USD** | MOEX | 0.018 | None (Insignificant) |
| **ETH-USD** | MOEX | 0.031 | Market Return (+) |

**Key Findings**

- Moderate levels of explanation for the variability in cryptocurrency returns based on market returns were suggested via an r-squared range from 0.260 to 0.364 across various indices (BTC & ETH).
- The p-values for the market returns (Markt_Ret) were below 0.05 at all lags and hence this is an indication that cryptocurrency returns are significantly related to market returns in line with existing literature.

- The shock variable of the geopolitical event (Russian invasion) showed a p-value > 0.05 for all transaction response variables, revealing no significant effect on cryptocurrency returns during that time horizon.

This suggests that in the Russia–Ukraine conflict, cryptocurrencies were more affected by general dynamics of traditional financial assets than through direct geopolitical channels. This contrasts with the notion that cryptocurrencies are safe assets to invest in during crises, where prior data shows they follow macro market trends more than geopolitical tension.

## 6.2 Correlation and Regression Analysis of Inflation and Cryptocurrency Prices

For the second objective, the study analysed the correlation between Russian and Ukrainian inflation rates with cryptoasset prices. Constructed regression models to effectively measure the impact inflation had on cryptocurrency prices over a 24-month period, starting from January 1st, 2022, and ending at January 1st of this year and figures 3 and 4 shows the inflation rate for that period against the price of BTC and ETH respectively.

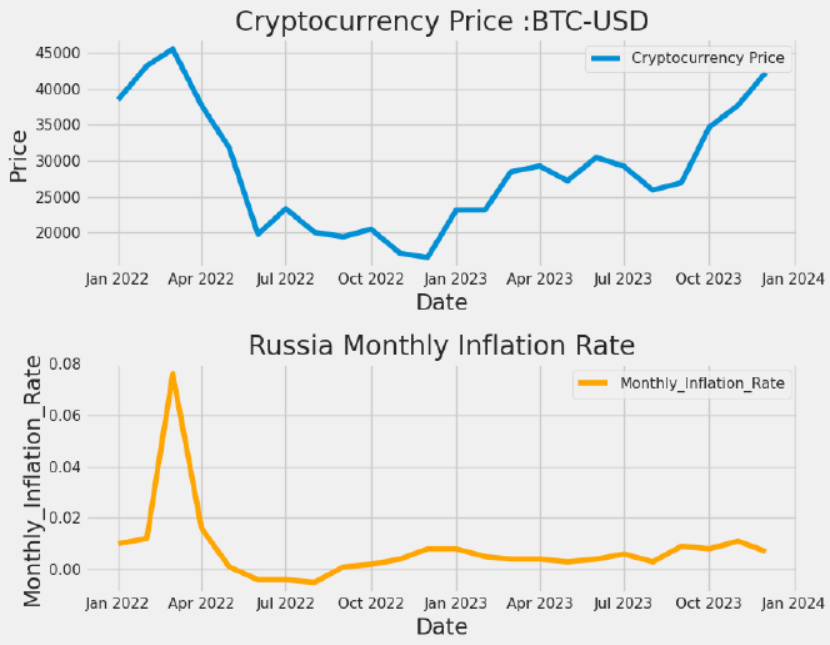


**Figure 3**: Plot of BTC Prices vs Inflation

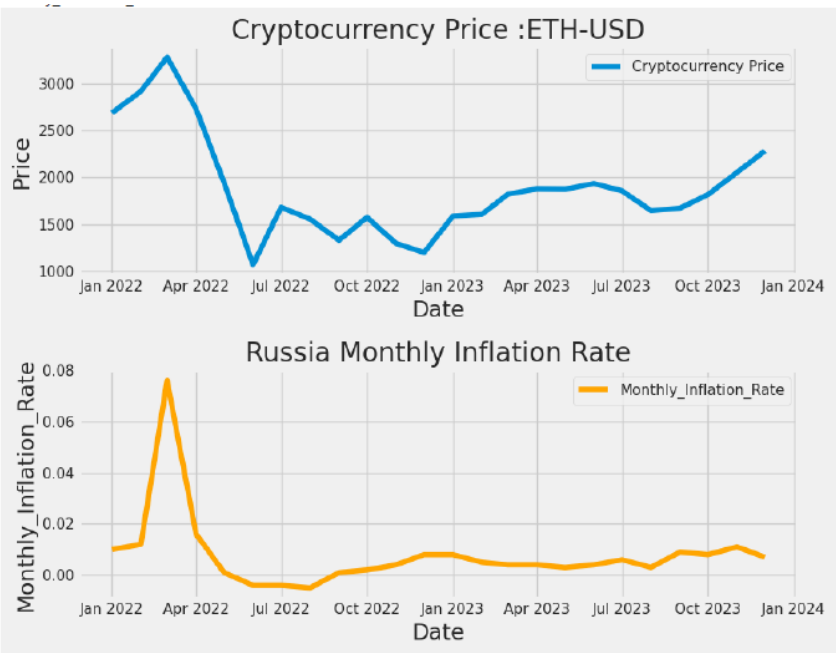


**Figure 4**: Plot of ETH Prices vs Inflation

**Ukraine Inflation**

| ***Cryptocurrency*** | ***$R^2$*** | ***Prob (F-statistic)*** | ***Coefficient (const/ Monthly_Inflation_ Rate)*** | ***p>\|t\|*** | ***Durbin-Watson*** | ***Cond. No*** | ***Correlation (Adj Close/Monthly_Inflation_Rate)*** |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.062* | *0.242* | *2.655e+04, 1.772e+05* | *0.000 , 0.242* | *0.304* | *85.3* | *0.248459* |
| *ETH-USD* | *0.119* | *0.0983* | *1682.5261, 1.58e+04* | *0.000 , 0.098* | *0.529* | *85.3* | *0.345402* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *SOL-USD* | *0.246* | *0.0137* | *25.9442, 1358.7017* | *0.008 , 0.014* | *0.481* | *85.3* | *0.495966* |
| *LTC-USD* | *0.024* | *0.472* | *77.1826, 266.5937* | *0.000 , 0.472* | *0.469* | *85.3* | *0.154158* |
| *DASH-USD* | *0.386* | *0.00119* | *35.7739, 1342.8888* | *0.000 , 0.001* | *0.668* | *85.3* | *0.621533* |
| *XRP-USD* | *0.012* | *0.614* | *0.4965, 1.2121* | *0.000 , 0.614* | *0.673* | *85.3* | *0.108395* |
| *DGB-USD* | *0.369* | *0.00164* | *0.0073, 0.3162* | *0.000 , 0.002* | *0.820* | *85.3* | *0.607648* |
| *XEM-USD* | *0.340* | *0.00279* | *0.0312, 1.3183* | *0.000 , 0.003* | *0.601* | *85.3* | *0.58302* |

**Russian Inflation Rate**

| Cryptocurrency | $R^2$ | Prob (F-statistic) | Coefficient (const/ Monthly_Inflation_Rate) | p>\|t\| | Durbin-Watson | Cond. No | Correlation (Adj Close/Monthly_Inflation_Rate) |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| BTC-USD | 0.339 | 0.00283 | 2.629e+04, 3.233e+05 | 0.000, 0.003 | 0.763 | 66.4 | 0.582262 |
| ETH-USD | 0.478 | 0.000183 | 1692.6856, 2.463e+04 | 0.000, 0.000 | 1.183 | 66.4 | 0.691407 |
| SOL-USD | 0.381 | 0.691407 | 33.1317, 1315.8553 | 0.000, 0.001 | 0.636 | 66.4 | 0.616904 |
| LTC-USD | 0.353 | 0.00219 | 74.3229, 800.4119 | 0.000, 0.002 | 0.812 | 66.4 | 0.594447 |
| DASH-USD | 0.442 | 0.000393 | 44.3111, 1118.5327 | 0.000, 0.000 | 0.486 | 66.4 | 0.664898 |
| XRP-USD | 0.417 | 0.000659 | 0.4679, 5.6199 | 0.000, 0.001 | 1.294 | 66.4 | 0.645473 |
| DGB-USD | 0.584 | 1.38e-05 | 0.4679, 5.6199 | 0.000, 0.000 | 0.454 | 66.4 | 0.764317 |
| XEM-USD | 0.400 | 0.000918 | 0.0395, 1.1131 | 0.000, 0.001 | 0.664 | 66.4 | 0.632205 |

**Key Findings**

- For the ruble inflation rate, strong correlation coefficients were achieved for cryptocurrency prices (in particular — XEM, DGB, DASH and SOL) from 0.582 to 0.764 with a positive sign of relationship.
- The correlation for Ukraine was positive as well but weaker in general, the coefficients being strongest again with DASH and somewhat less strong with DGB.
- The regression models produced R-squared values in Russia (up to 0.584 for DGB-USD) that were higher than those recorded in Ukraine (up to 0.386 for DASH-USD), suggesting that inflation rates

had a stronger effect on cryptocurrency price changes in the former country, even if this action was indirect by affecting fiat exchange rate fluctuations.

These results highlight why cryptocurrencies may become a store of value for inflation, especially under the circumstances that are taking place in Russia during this geopolitical conflict. The high correlation in Russia indicates that investors there saw cryptocurrencies as an instrument for keeping their capital against hyperinflation and the depreciation of a national currency. This underscores the dual nature of cryptocurrencies, both as speculative instruments vulnerable to market movements and alternative value stores amidst macroeconomic uncertainty.

### 6.3 Comparative Analysis Across Market Indices

In the last objective, the study checked how market indices affect the return of cryptocurrencies in different global markets (S&P 500, NASDAQ, DAX, CAC 40; NIKKEI, TSX and MOEX). The research sought to answer whether market returns move cryptocurrencies differently in distinct economic areas.

**Key Findings**

- BTC and ETH showed the strongest correlations with cryptocurrency returns, which was consistent across all market indices, particularly S&P 500 and NASDAQ.
- On the other hand, MOEX represented the weakest correlation of any index relative to its global counter parts which would suggest that during this conflict overall returns for cryptocurrencies are likely being impacted less so by moves in Russia.

This comparison further illustrates that the presence of conflict will not override global perception of cryptocurrency value matching those in financial markets such as the USA.

### 6.4 Discussion

By focusing on investigating the impact of geopolitical tensions, especially Russia-Ukraine conflict on the cryptocurrency markets' through using Capital Asset Pricing Model (CAPM) new insights were found.

Nevertheless, as all empirical research, this evidence must be interpreted cautiously taking into account the limitations of the study and areas where enhancements could strengthen confidence in these results.

The use of the CAPM for systematic risk analysis on cryptocurrency returns due to market return and geopolitical shock offer an organised view into these emerging asset classes. This is a new ground concerning the application of an established financial model that traditionally only is used in more developed markets; even though this adaptation to cryptos proves innovative, it presents a challenge. The most significant outcome that market returns significantly affect cryptocurrency returns for different indices (e.g., S&P 500, NASDAQ, TSX) corresponds with established financial theories that suggest a correlation between market sentiments and asset performance. Despite this, the model applied to cryptocurrencies, which are highly volatile and traded speculatively than other tradable assets may not fully encapsulate these digital (crypto) assets.

But one major drawback is that it assumes a linear association between the independent variables (market returns and geopolitical shocks) and dependent variable (cryptocurrency returns). In particular, for periods of financial collapse CAPM may not capture the non-linear behaviour of cryptocurrency returns (e.g., non-normality). For example, $R^2$ values are often quite low (eg.; 0.092 for BTC-USD using the DAX index), meaning that the model accounts for only a tiny fraction of cross-sectional variation in cryptocurrency returns. This indicates that other, possibly nonlinear factors are more important.

The shock window of 10 days might also be too short for key geopolitical events in the west, such as invasion into Ukraine by Russia and the announcement of SWIFT sanctions may not fully encapsulate the prolonged effects of these shocks on cryptocurrency markets (Makhlouf & Selmi, 2022). Geopolitical events create ripple effects and an extra dynamic modelling approach like using a rolling window analysis which could provide a better grasp of how these stocks impact the behaviour of the market over a period (Aysan et al., 2019).

The results in general are consistent with previous studies (Kamal & Wahlstrøm, 2023; Nittayakamolphun et al., 2024) on financial markets reacting to geopolitical tensions and specific about the behaviours of cryptocurrencies as a new type of assets. Whereas traditional assets like equities and bonds have history-backed views on how they could respond to certain geopolitical risks (Jung et al., 2021), cryptocurrencies have not been around as long — so it's more a wildcard unto itself relatively. The strong, positive relationship of market returns, and cryptocurrency returns means that despite their decentralisation, cryptocurrencies remain subject to broader financial conditions.

This finding is largely in line with research suggest that the sensitivity of financial markets to geopolitical tensions, but they also highlight the unique characteristics of cryptocurrencies as an asset class (Long et al., 2022). That said, the shock variable is mostly not significant for cryptocurrencies returns which contradicts this study's hypothesis that cryptocurrencies are a hedge against geopolitical risks. The result is significant because it contradicts the view that some digital currencies, such as Bitcoin and Ethereum, could serve as safe haven assets as justified in Conlon et al. (2020).

In terms of the study's methodology, specifically for cryptocurrencies and market indices covered by the study, it was quite sound as those are some of highly recognisable digital assets in consideration with major benchmarks. Despite this, the lack of some minor cryptocurrencies in the main analysis although they can be a valuable indicator concerning specific geopolitical context might not necessarily be representative of the overall results. For example, smaller market capitalisations coins could be affected differently by geopolitical shock to have a better understanding of the whole market trends (Long et al., 2022).

A final important note about the methodology is that it uses CAPM, which might be powerful but suffers from many assumptions that do not appear to hold in cryptocurrency markets. An example, the CAPM assumes all investors have equal access to information and markets are efficient (O'Sullivan, 2018). Unfortunately, the cryptocurrency market is one where information asymmetry runs rampant and due to insider trading, crypto manipulation, high frequency trading can lead to substantial deviations from CAPM's predictions (Park & Chai, 2020).

Additionally, the model supposes that market returns have a constant relationship with asset returns for all time periods — an assumption unlikely to hold true in cryptocurrency markets. Given technological improvements, regulatory changes and changing market sentiment, these assets are expected to be dynamic in nature making an approach that adapts over time more suitable for assessing risk (Wronka, 2024). Future works might be greatly boosted by applying more advanced statistical models, like a GARCH model that deals with volatility clustering and probably represents the unique risk dynamics of cryptocurrencies much better.

## 7.0 Conclusion and Future Work

This study focused on the effect of geopolitical turbulence in cryptocurrency markets by studying the Russia-Ukraine crisis. The aims are to investigate the bidirectional association between geopolitical tensions and systematic risks in bitcoin prices; and evaluate how inflation occurring within Russia and Ukraine can affect public's demand for cryptocurrencies as an informal hedge against currency devaluation.

This would include an analysis of whether alternative effects exist between small, mid- or large cap stocks and interest rates measured by FED rate hikes using both the CAPM (Capital Asset Pricing Model) as well correlation. The results showed that although the cryptocurrency returns are seriously affected by market factors, they seem less so based on geopolitical shocks further challenging their status as a crisis hedge. The findings also emphasized the close relationship between inflation and cryptocurrency prices, particularly Russia's.

The research was limited, as expected from any alpha based CAPM model and exclusions to less known cryptocurrencies. These may have limited the generalizability of the findings. It would also be useful to extend the model based on non-linear models like GARCH that can handle volatility in cryptocurrencies. Moreover, using more cryptocurrency types and a longer time span can make the results more informative. Combining qualitative data on investor sentiment with a mixed-methods approach would be an especially fruitful way of deepening insights into how markets experience geopolitical events. This is providing a basis for more detailed investigations to continue the refinement of models and investigation into cryptocurrencies considering global uncertainties.

Link to Google Drive:

https://drive.google.com/drive/folders/19Ep1OiYdj-nkgqhj43ZzbnZnBJa9dsXk?usp=drive_link

Link to ppt video presentation:

https://studentncirl-my.sharepoint.com/:v:/r/personal/x22229001_student_ncirl_ie/Documents/Recordings/Analytical%20Review%20of%20Cryptocurrency%20Dynamics%20in%20Geopolitical%20Conflicts_%20A%20Case%20Study%20of%20the%20Ukraine-Russia%20Conflict-20240820_045019-Meeting%20Recording.mp4?csf=1&web=1&e=DJlGCN

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APPENDICES

The result for other cryptocurrency using S&P500 are shown in the table below:

S&P500

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.333* | *1.64e-22* | *-0.0010, 1.3670, -0.0109* | *0.600, 0.000, 0.221* | *2.061* | *67.9* | *0.57328, -0.065597, -0.003481* |
| *ETH-USD* | *0.330* | *2.95e-22* | *-0.0011, 1.8099, -0.0086* | *0.652, 0.000, 0.467* | *2.030* | *67.9* | *0.572807, -0.039897, -0.003481* |
| *SOL-USD* | *0.238* | *2.14e-15* | *-0.0069, 2.3279, -0.0031* | *0.083, 0.000, 0.870* | *1.961* | *67.9* | *0.488225, -0.010779, -0.003481* |
| *LTC-USD* | *0.254* | *1.65e-16* | *0.0005, 1.6360, -0.0160* | *0.854, 0.000, 0.219* | *1.959* | *67.9* | *0.499482, -0.069302, -0.003481* |
| *DASH-USD* | *0.214* | *1.15e-13* | *-0.0025, 1.5735, -0.0069* | *0.393, 0.000, 0.617* | *1.912* | *67.9* | *0.461296, -0.029816, -0.003481* |
| *XRP-USD* | *0.211* | *1.84e-13* | *0.0004, 1.4875, -0.0046* | *0.881, 0.000, 0.730* | *2.149* | *67.9* | *0.458495, -0.021123, -0.003481* |
| *DGB-USD* | *0.284* | *9.90e-19* | *-0.0025, 2.0450, -0.0147* | *0.430, 0.000, 0.325* | *2.177* | *67.9* | *0.530446, -0.054857, -0.003481* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *XEM-USD* | *0.268* | *1.52e-17* | *-0.0042, 1.8385, -0.0117* | *0.150, 0.000, 0.401* | *2.140* | *67.9* | *0.515885, -0.047534, -0.003481* |

NASDAQ

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.364* | *4.44e-25* | *-0.0008, 1.0787, -0.0089* | *0.646, 0.000, 0.306* | *2.034* | *51.2* | *0.600903, -0.065597, -0.022760* |
| *ETH-USD* | *0.353* | *3.41e-24* | *-0.0009, 1.4135, -0.0060* | *0.702, 0.000, 0.606* | *1.973* | *51.2* | *0.593747, -0.039897, -0.022760* |
| *SOL-USD* | *0.258* | *8.76e-17* | *-0.0067, 1.8258, 0.0003* | *0.090, 0.000, 0.989* | *1.932* | *51.2* | *0.507769, -0.010779, -0.022760* |
| *LTC-USD* | *0.284* | *9.72e-19* | *0.0007, 1.3066, -0.0135* | *0.799, 0.000, 0.288* | *1.929* | *51.2* | *0.530101, -0.069302, -0.022760* |
| *DASH-USD* | *0.237* | *2.73e-15* | *-0.0023, 1.2502, -0.0046* | *0.419, 0.000, 0.736* | *1.906* | *51.2* | *0.486409, -0.029816, -0.022760* |
| *XRP-USD* | *0.222* | *3.22e-14* | *0.0006, 1.1509, -0.0024* | *0.837, 0.000, 0.853* | *2.173* | *51.2* | *0.470649, -0.021123, -0.022760* |
| *DGB-USD* | *0.308* | *1.59e-20* | *-0.0023, 1.6055, -0.0118* | *0.464, 0.000, 0.424* | *2.164* | *51.2* | *0.553042, -0.054857, -0.022760* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *XEM-USD* | *0.285* | *8.97e-19* | *-0.0040, 1.4290, -0.0091* | *0.164, 0.000, 0.510* | *2.143* | *51.2* | *0.53244, -0.047534, -0.022760* |

DAX

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.092* | *3.89e-06* | *-0.0020, 0.7474, 0.0005* | *0.349, 0.000, 0.963* | *2.177* | *71.6* | *0.303945, -0.043455, -0.151847* |
| *ETH-USD* | *0.093* | *3.46e-06* | *-0.0024, 0.9997, 0.0045* | *0.391, 0.000, 0.730* | *2.080* | *71.6* | *0.304632, -0.025976, -0.151847* |
| *SOL-USD* | *0.041* | *0.00443* | *-0.0083, 1.0143, 0.0113* | *0.059, 0.001, 0.582* | *2.089* | *71.6* | *0.200427, 0.002800, -0.151847* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *LTC-USD* | *0.066* | *0.000148* | *-0.0015, 0.8779, -0.0016* | *0.613, 0.000, 0.912* | *2.077* | *71.6* | *0.257455, -0.045667, -0.151847* |
| *DASH-USD* | *0.037* | *0.00788* | *-0.0039, 0.6916, 0.0072* | *0.220, 0.002, 0.628* | *2.103* | *71.6* | *0.190031, 0.000478, -0.151847* |
| *XRP-USD* | *0.044* | *0.00317* | *-0.0002, 0.7065, 0.0050* | *0.943, 0.001, 0.722* | *2.248* | *71.6* | *0.208122, -0.010129, -0.151847* |
| *DGB-USD* | *0.064* | *0.000201* | *-0.0035, 1.0113, 0.0013* | *0.315, 0.000, 0.936* | *2.269* | *71.6* | *0.253107, -0.033603, -0.151847* |
| *XEM-USD* | *0.082* | *1.57e-05* | *-0.0055, 1.0680, 0.0057* | *0.088, 0.000, 0.707* | *2.148* | *71.6* | *0.286321, -0.021229, -0.151847* |

CAC 40

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.098* | *1.87e-06* | *-0.0021, 0.7980, -0.0007* | *2.233, 0.000, 0.942* | *2.233* | *74.4* | *0.312278, -0.043455, -0.125390* |
| *ETH-USD* | *0.104* | *7.63e-07* | *-0.0026, 1.0960, 0.0032* | *0.349, 0.000, 0.806* | *2.132* | *74.4* | *0.321885, -0.025976, -0.125390* |
| *SOL-USD* | *0.051* | *0.00116* | *-0.0086, 1.1731, 0.0104* | *0.050, 0.000, 0.609* | *2.126* | *74.4* | *0.224162, 0.00280, -0.12539* |
| *LTC-USD* | *0.070* | *8.89e-05* | *-0.0017, 0.9376, -0.0029* | *0.574, 0.000, 0.834* | *2.105* | *74.4* | *0.264303, -0.045667, -0.125390* |
| *DASH-USD* | *0.051* | *0.00127* | *-0.0041, 0.8398, 0.0069* | *0.193, 0.000, 0.638* | *2.134* | *74.4* | *0.223034, 0.000478, -0.125390* |
| *XRP-USD* | *0.044* | *0.00306* | *-0.0003, 0.7360, 0.0037* | *0.911, 0.001, 0.790* | *2.273* | *74.4* | *0.209278, -0.010129, -0.125390* |
| *DGB-USD* | *0.070* | *8.80e-05* | *-0.0037, 1.0993, -0.0001* | *0.287, 0.000, 0.995* | *2.310* | *74.4* | *0.264753, -0.033603, -0.125390* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *XEM-USD* | *0.092* | *4.36e-06* | *-0.0057, 1.1691, 0.0042* | *0.075, 0.000, 0.778* | *2.180* | *74.4* | *0.302171, -0.021229, -0.125390* |

Nikkei

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.003* | *0.716* | *-0.0014, -0.0257, -0.0093* | *0.563, 0.894, 0.418* | *2.093* | *84.0* | *-0.007067, -0.052714, -0.031619* |
| *ETH-USD* | *0.002* | *0.747* | *-0.0023, 0.1757, -0.0047* | *0.456, 0.492, 0.755* | *2.068* | *84.0* | *0.045555, -0.021845, -0.031619* |
| *SOL-USD* | *0.000* | *0.982* | *-0.0087, -0.0604, -0.0025* | *0.065, 0.876, 0.911* | *2.138* | *84.0* | *-0.010009, -0.006955, -0.031619* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *LTC-USD* | *0.001* | *0.850* | *-0.0020, -0.0386, -0.0088* | *0.539, 0.885, 0.579* | *2.217* | *84.0* | *-0.008346, -0.036010, -0.031619* |
| *DASH-USD* | *0.003* | *0.725* | *-0.0044, 0.1865, 0.0071* | *0.186, 0.495, 0.659* | *2.050* | *84.0* | *0.043759, 0.027410, -0.031619* |
| *XRP-USD* | *0.000* | *0.988* | *-0.0003, -0.0286, 0.0015* | *0.926, 0.908, 0.917* | *2.259* | *84.0* | *-0.007802, 0.007053, -0.031619* |
| *DGB-USD* | *0.001* | *0.930* | *-0.0033, -0.0411, -0.0067* | *0.379, 0.895, 0.718* | *2.213* | *84.0* | *-0.007921, -0.023381, -0.031619* |
| *XEM-USD* | *0.003* | *0.723* | *-0.0056, 0.2309, -0.0001* | *0.110, 0.421, 0.995* | *2.117* | *84.0* | *0.052653 -0.002053, -0.031619* |

TSX

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.260* | *4.87e-17* | *-0.0009, 1.8434, -0.0125* | *0.643, 0.000, 0.181* | *2.129* | *104* | *0.505062, -0.067011, 0.012071* |
| *ETH-USD* | *0.249* | *3.23e-16* | *-0.0014, 2.4091, -0.0103* | *0.588, 0.000, 0.409* | | *104* | *0.497045, -0.039390, 0.012071* |
| *SOL-USD* | *0.156* | *6.41e-10* | *-0.0065, 2.8690, -0.0060* | *0.118, 0.000, 0.763* | *2.013* | *104* | *0.395024, -0.012793, 0.012071* |
| *LTC-USD* | *0.194* | *2.03e-12* | *0.0001, 2.1972, -0.0174* | *0.967, 0.000, 0.199* | *2.036* | *104* | *0.434854, -0.068050, 0.012071* |
| *DASH-USD* | *0.175* | *3.90e-11* | *-0.0026, 2.1830, -0.0086* | *0.373, 0.000, 0.546* | *2.050* | *104* | *0.417012, -0.029785, 0.012071* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *XRP-USD* | *0.137* | *1.03e-08* | *0.0011, 1.8335, -0.0068* | *0.701, 0.000, 0.620* | *2.177* | *104* | *0.369403, -0.024784, 0.012071* |
| *DGB-USD* | *0.190* | *3.82e-12* | *-0.0023, 2.5549, -0.0171* | *0.493, 0.000, 0.281* | *2.201* | *104* | *0.431948, -0.056334, 0.012071* |
| *XEM-USD* | *0.204* | *4.54e-13* | *-0.0039, 2.4519, -0.0141* | *0.202, 0.000, 0.332* | *2.093* | *104* | *0.448419, -0.049567, 0.012071* |

MOEX

| *Cryptocurrency* | $R^2$ | *Prob (F-statistic)* | *Coefficient (const, Markt_Ret, Shock)* | *p>\|t\|* | *Durbin-Watson* | *Cond. No* | *Correlation (Inv_Ret/ Markt_Ret, Inv_Ret,Shock, Markt_Ret,Shock)* |
|---|---|---|---|---|---|---|---|
| *BTC-USD* | *0.018* | *0.116* | *-0.0013, 0.2090, -0.0059* | *0.561, 0.038 0.681* | *2.113* | *45.5* | *0.132696, 0.001172, 0.205703* |
| *ETH-USD* | *0.031* | *0.0264* | *-0.0020, 0.3588, -0.0024* | *0.495, 0.008, 0.902* | *2.094* | *45.5* | *0.175075, 0.028214, 0.205703* |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *SOL-USD* | *0.020* | *0.0944* | *-0.0077, 0.4331, -0.0034* | *0.088, 0.032, 0.906* | *2.199* | *45.5* | *0.141400, 0.205703* | *0.021607,* |
| *LTC-USD* | *0.020* | *0.0962* | *-0.0010, 0.3026, -0.0068* | *0.748, 0.031, 0.735* | *2.081* | *45.5* | *0.139314, 0.205703* | *0.007106,* |
| *DASH-USD* | *0.023* | *0.0675* | *-0.0036, 0.2644, 0.0191* | *0.247, 0.060, 0.341* | *2.092* | *45.5* | *0.138019, 0.205703* | *0.088866,* |
| *XRP-USD* | *0.016* | *0.144* | *0.0007, 0.2387, 0.0101* | *0.824, 0.080, 0.603* | *2.258* | *45.5* | *0.123806 0.205703* | *0.058578,* |
| *DGB-USD* | *0.031* | *0.0252* | *-0.0025, 0.4174, 0.0014* | *0.474, 0.008, 0.950* | *2.199* | *45.5* | *0.176345, 0.205703* | *0.040242,* |
| *XEM-USD* | *0.020* | *-0.0036, 0.3089, 0.0041* | | *0.288, 0.043, 0.849* | *2.262* | *45.5* | *0.137500, 0.205703* | *0.040386,* |