The Influence of Fintech and Technology Stock Indices on Cryptocurrencies Dynamics: A Quantile Regression Approach

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Abstract

This study examines the asymmetric and nonlinear linkages between the major cryptocurrencies of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP) and the major financial indices of KBW NASDAQ Financial Technology Index and the Dow Jones Global Technology Index using Quantile-on-Quantile Regression (QQR).We investigate how bitcoin responds to the financial indices in different quantiles of the return distribution using a monthly time-series data set January 01, 2020 to December 31, 2024. Cryptocurrencies provide strong responses on quantile conditional dependence, illustrating how various market conditions impact other financial variables. These impacts emphasize the diversification and risk amplification features of cryptocurrencies and are especially evident at times of excessive market optimism and pessimism. The paper also highlights the necessity of keeping an eye on the connections between crypto assets and the financial industry in order to provide suitable regulatory responses to dangers that emerge in a sector that has been seeing significant growth. The findings of the correlation between traditional financial markets and the digital asset ecosystem will likely teach investors, policymakers, and regulators a lot.

Key words: C*ryptocurrencies, Quantile-on-Quantile, asymmetric, Fintech, Global technology.*

Introduction

Financial Technology (Fintech) has grown rapidly in response to the impact of technological improvements on financial markets. Fintech has been seen as an alternative for the drawbacks of conventional financial market operations. The use of crypto currencies and block chain technology has grown concurrently in financial markets, determining them as improvements in the traditional financial systems (Allen, Gu, and Jagtiani 2022; Chowdhury et al. 2023; Naeem et al. 2023). In this development a great deal of interest has been expressed by scholars, investors and lawmakers. The relationships between technology-driven securities such fintech developments and cryptocurrency markets must be examined as investors actively look for new techniques for risk diversification and better investment outcomes.

A dynamic collaboration with traditional markets for stocks has been introduced by the emergence of digital currencies which have significantly altered the financial sector. The purpose of this study is to investigate empirically with an emphasis on estimated volatility and the asymmetric effects of digital currencies on the major equities markets in developed economies. This research is significant because digital currencies BTC, XRP, BNB are becoming more and more popular as perspective trade currencies as well as speculative assets. Lin et al. (2025) find that large and small Treasury yields and exchange rates on USD are significantly related to Bitcoin returns in different quantiles. Although a number of digital currency related topics have been thoroughly studied, such as their technological framework and possible impact on future financial systems limited have been learned about their complex and irregular impacts on equity markets especially when examined through the perspective Quantile on Quantile Regression Analysis.

The advancement of technology has presented new opportunities for financial markets and promoted the development of economic and efficiency boosting solutions (LE, Abakas and Tiwari, 2021). Likewise, the inclusion of block chain-based assets brings an entirely new perspective to the subject of financial assets. These assets provide investors and policymakers with more options for diversification because of their robust security features and low correlation with traditional assets.

The increasing popularity of digital money transfer, Fintech, cryptocurrency and other technological development is causing major changes in the global economy and traditional financial system. Specifically, after the introduction of cryptocurrencies demonstrates how technology revolution for traditional financial system and these digital currencies are protected due to by using encryption security system. To forecast tail risks of cryptocurrencies (Xu et al. 2023) introduce a productive quantile model averaging. Due to digital money and digital financial transfers globally financial markets have been significantly changing and before the introduction of BTC the digital financial transfer services were expensive and slow. The international monetary fund states that electronic digital currency is precisely the same as electronic money (Yang et al., 2020).

Digital currencies have been extensively studied in a number of areas such as the technological framework and their possible impact on future financial systems. However, when quantile regression analysis is used there is limited study about their complexities and irregular effects on equity market. Singh et al. (2023) identify an improved accuracy in risk prediction on a set of cryptocurrencies using a hybrid quantile regression neural network (MCQRNN) that includes macrofinancial factors. Their strategy is in accordance with current research that explores the complexity of digital currencies and how they affect financial markets highlighting the different view pints provided by quantile regression technique (Baur er at., 2018; Corbet et at., 2019).

This study aims to examine the relationship between crypto-currencies, Fintech index and global technology index by employing quantile techniques. The data was gathered from numerous sources, for instance cryptocurrencies, fintech index and global tech index, quantile technique was applied to that data and the final results were interpreted to offer insights to policymakers and investors in the fintech industry.

We have employed quantile regression analysis to investigate this further in our analysis focusing on how digital currencies influence traditional financial markets at different development levels. This is an interesting finding as it reflects the potential channel through which digital currencies influence KBW fintech index and Dow Jones Global Technology Index also this study could provide valuable insights to investors and policymakers. It was shown by Umer et al. (2022) Bitcoin and stock market returns show positive effects and negative correlations presented using quantile regression. This study highlights the need for quantile regression to understand the complexities of these relationships and integrates the current discussion on the evolving financial landscape.

The purpose of the research we conducted is to use quantile regression analysis to better understand how shifts in digital currencies impact traditional equities markets at various distribution levels. By exposing the complex connections between digital currency movements and fintech index and this study may provide insightful information to policymakers and investors. Umer et al. (2022) examined the relationship between Bitcoin and stock market returns using quantile regression finding positive effects and negative correlations. Our research highlights the significance of quantile regression in capturing the intricacies of these interactions and adding the continuing discussions regarding the changing dynamics of modern finance.

Problem Statement

The growing popularity of cryptocurrencies has been linked to their simultaneous movement with other indexes such as the KBW Nasdaq Financial Technology Index and Dow Jones Global Technology Index. When developing the regulatory environment this poorly understood correlation makes it difficult for policymakers and fintech investors to create effective investments strategies.

This study uses a Quantile-on-Quantile regression analysis approach to examine the relationship between cryptocurrencies, KBW Nasdaq Financial Technology Index and Dow Jones Global Technology Index. In addition to providing useful information regarding the correlation of various financial assets, this closes a significant research gap and has applications for fintech investors and policymakers.

This study uses a method that can identify correlation over a variety of timescales unlike other research on the connections between cryptocurrencies and other financial assets that had difficulty adequately describing these relationships. This method allows one to understand how cryptocurrencies and other financial assets have moved together over different time periods in a more detailed and advanced manner.

Research Questions

What does the Quantile-on-Quantile Regression Analysis tell us about the time varying association between cryptocurrency prices and developed market stock indices at specified quantiles?

How the Quantile-on-Quantile Regression Analysis that the impact of the KBW Nasdaq Fintech Technology Index on Cryptocurrencies price distributions at different quantile levels is discovered?

What does the Quantile-on-Quantile Regression Analysis expose regarding the Dow Jones Global Technology Index impact on the volatility on the cryptocurrency market?

Purpose of this study

For the purpose to address this research gap the current study uses quantile analysis approaches to examine two correlations across a wide range of time scales between cryptocurrencies, KBW Nasdaq Financial Technology and Dow jones Global Technology Index. Regulators and investors in downstream technology might profit from these insights. The goal of this study is to help investors and policymakers create well thought out strategies and policies by identifying correlation and linkages of various financial assets.

This study aims to explore the implications of correlations for policymaking in an effort to contribute to the previously mentioned challenges. The study's findings and recommendations are particularly significant to policymakers who seek to pursue efficient and successful regulatory structures related to cryptocurrencies and other financial assets. The study aims to give investors and governments worldwide a picture of how cryptocurrencies and other assets move together.

The authors came to an understanding that there are many different time horizons and intricate dynamics underlying the correlation of cryptocurrencies and other financial assets. Strong correlations have been found, and anyone looking to develop investment portfolios and make money can benefit from these correlations. These insights could be helpful as a guide for policymakers who want to regulate cryptocurrencies alongside other financial assets and when it comes to understanding how these correlations may impact the stability of the global financial system.

Significant of the Study

The main benefit of this research is the examination of the relationship between cryptocurrencies and other index such as KBW Nasdaq Fintech Index and Dow Jones Global Technology Index using the quantile technique. The study addresses and closes the gap in literature by offering useful information about the challenging and fluctuating relationships between these variables which will provide help to investors and policymakers.

Finding the ways that cryptocurrencies and other financial assets move together across different time periods was the main objective of the study. This information becomes essential for investors and policymakers in the fintech industry. Regardless, the research also has academic value since it adds recent data and information in existing knowledge which is normally more focused on traditional assets like stocks and bonds. By examining the relationship between cryptocurrencies which have been rapidly gaining popularity, this study adds the new pool of knowledge in literature.

Its practical significance resided in the consequences of this research for investment and policymaking strategies. These results will help investors develop investing strategies that are more probably to be effective because they are developed after accounting for the co-operation of other financial indexes and cryptocurrencies. As it allows them to analyze the effects of their co movements on financial stability and it will also help policymakers establish more effective regulations for cryptocurrencies and other assets.

It is expected that these results will further knowledge of the relationships between cryptocurrencies and other assets as well as the effects of these relationships on investment strategies and policy decisions. Both industry and academia will benefit from these findings which have the potential to influence global financial markets.

Literature Review

Significant advantages have been demonstrated by this creative integration of technology into financial institutions' operations. A number of studies demonstrate the significant part that financial technological advances have played in a variety of economies. However, Foroni et al. (2023) analyzed the order of regime switching with a specific focus on cryptocurrency market using hidden Markov quantile model with copula to detect the independent structure dependence at both normal as well as crisis segment of COVID-19 pandemic. Enhancing the performance of the banking industry and encouraging the development of financial systems have been made possible by data driven and effective methods of transaction and financial service execution (Jiao et al. & Su et al. 2021). Fintech saw unprecedented expansion throughout the fourth industrial revolution with a growing and substantial quantity of investments and return on investments.

Additionally, fintech is widely recognized for automating and protecting business procedures for providers of financial services, particularly banks have demonstrated its value by increasing profits and operational effectiveness. A positive relationship between fintech adoption and SME's efficiency was found using the Generalized Method of Moments GMM technique by (Abbasi et al 2020) indicating the establishment of fintech startups to improve SME's performance more significantly.

In the past few years' cryptocurrency has become incredibly popular with the general public, investors, scholars and policymakers. Bitcoin is a combination of financial and commodity money that has no intrinsic value, while it is not governed by any government or authority (Conlon, et al. 2020). The study looked at the current use of bitcoin and its potential future uses based on its features as well as whether it is an asset of just a medium of exchange (Blau, et al. 2021).

In present financial study cryptocurrencies, the fintech index and the global technology index are frequently significant topics. When combined these offer insight into different aspects of digital financial ecosystems, the technological developments which motivate them and the developments that influence the economy as overall.Regarding market efficiency, Takaishi (2025) pointed out that COVID-19 introduced a structural break that altered the volatility structure and fractal dimension of Ethereum and Bitcoin, primarily in terms of return and volatility innovations between different stockmarkets and cryptomarkets.

We investigate into the relationships between each of these variables to teach more about their co movements any cross correlative horizontal movements and the significance of these for investment strategies and market health. The research investigated examines how cryptocurrencies are interconnected with fintech innovations and the performance of the major technology companies listed on the Dow Jones in order to provide insights to investors, policymakers and other stakeholders in the financial and technology sectors.

This literature highlights the importance to understand how cryptocurrency, KBW Nasdaq fintech index and DJ global technology index correlated with in the global financial ecosystem. A potential approach to cutting down various factors and examining the complex relationships between these variables is the wavelet analysis methodology.

Empirical Review

The relationships between other financial factors including cryptocurrencies, fintech indices and international technology indexes like Dow Jones have been examined in earlier research. Quantile analysis has not been used much to evaluate these relationships. The correlations between these factors have been simplified down into distinct frequency bands using quantile analysis in this study which closes this gap and provides insightful information for fintech investors and tech focused regulators (Abakah, Tiwari, et al 2023).

The findings indicate a significant positive correlation between cryptocurrencies, KBW Nasdaq fintech indices and Dow Jones global technology indexes across all frequency bands. There is a lower correlation between cryptocurrency prices and the Dow Jones global technology index at lower frequencies while high frequency studies indicate a positive correlation between cryptocurrency prices and the fintech index. Furthermore, the index that included fintech companies also showed a strong association with the global technology index.

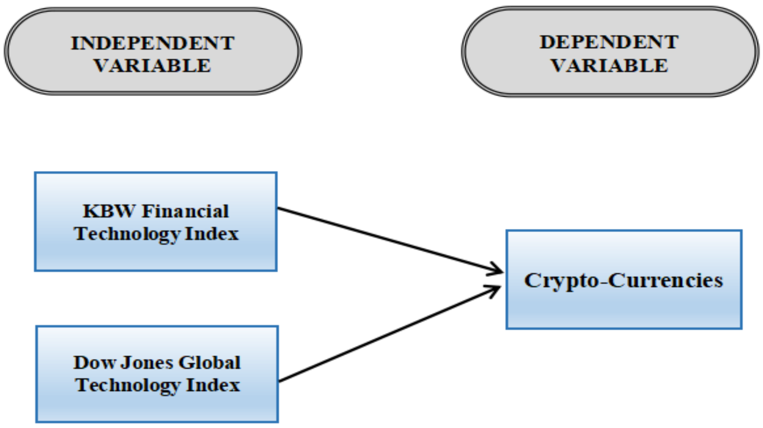
This study expands on previous studies by examining the relationships between these variables and highlights the significance of their chorological and spectral behavior. With significant implications for investment strategies and regulatory frameworks this work highlights the value of frequency band analysis in comprehending the co movement between financial and technology indexes.

The co-movement and correlations between cryptocurrencies, fintech and global technology indices were deconstructed and analyzed using quantile analysis which proved to be reliable technique. The results can assist policymakers and investors in making well informed decisions about economic policy options and investments with a technological focus.

Hypothesis

- **H1:** Significant relationship between KBW Nasdaq Financial Technology Index and cryptocurrency prices.
- **H2:** Significant correlation between currency pairs and Dow Jones Global Technology Index.
- **H3:** Co-movement and Correlation of crypto-currencies, KBW Nasdaq Fintech Index and Dow Jones Global Technology Index can be effectively decomposed and analyzed using the Quantile-on-Quantile Regression Analysis**.**

Figure 1
Research Framework



Research Methodology

This section will explain specific methods utilized to gather and examine the data for the purpose of this research. This study aims to determine the links between the co-movement of cryptocurrencies, KBW Nasdaq fintech indices and the Dow Jones Global Technology Index through using quantile analysis.

Choosing a methodology that is appropriate for the goals and objectives of the research is important. This study has chosen quantile on quantile 3D analysis as the appropriate methodology for examining the chronological and spectral characteristics of the co movement of these variables since it is the most effective method for studying time series data. Quantile-on-Quantile regression (QQR) is especially well suited for the modeling of volatile financial data e.g., cryptocurrency returns, since it relaxes several assumptions of Ordinary Least Squares (OLS). QR does not assume normality of the errors nor is uniformity necessary among observations, unlike OLS which does have the assumptions of normality, homoscedasticity and linear links. A better understanding of how co-variates influence the outcomes is obtained via QQR's revealing on the varying effects at numerous quantiles of the conditional distribution as evidenced from works such as Francis & Nwakuya 2022; Wang & Zhou, 2023; Youssef & Latif 2023. In addition, QQR is resistant to outliers and heavy tails, the common feature of financial time series, as the function instead minimizes the absolute deviations, rather than the square deviations. In our investigation in which returns in cryptocurrencies have nonlinear dependence, volatility clustering and skewness, that QQR and thus, QQR is an attractive tool. By modeling the cross-quantile dynamics that are completely ignored by OLS, QQR enhances by simulating the effects of different quantiles of financial indexes on different quantiles of cryptocurrency returns.

Using robust and systematic methods such as research is credible. Market and time series data on cryptocurrencies, fintech indices and the Dow Jones Global Technology index was gathered from reliable sources investing.com and then analyzed. The correlation of these variables was identified using the quantile regression technique by decomposing the data into different frequency bands.

It's important to constantly identify and resolve any possible research limitations. The accuracy and completeness of the data sources as well as confounding variables that affect how the variables in this study relate to one another may provide challenges. The data sources have been carefully selected, and an extensive data cleaning procedure was carried out to ensure accuracy in order to reduce these risks. In order to determine the effect of any confounding variables on the outcome we also conducted a sensitivity analysis.

In conclusion, this research technique uses quantile regression analysis to examine the functions that are involved in studying the co-movement of cryptocurrencies with fintech index and the Dow Jones Global Technology index. For fintech investors and policymakers the study provides valuable insight into the spectral and historical links around these financial statistics with accurate information.

Research Approach

The article "Examining the Impact of KBW Nasdaq Fintech Index and Dow Jones Global Technology Index on Cryptocurrencies Dynamics: A Quantile Regression Approach" would take an exploratory research approach on the basis of the information provided.

Data Collection Procedure

This section explains the procedures used to gather data for the study "Examining the Impact of KBW Nasdaq Fintech Index and Dow Jones Global Technology Index on Cryptocurrencies Dynamics: A Quantile Regression Approach". The underlined information is discussed for this study: -

Study Population:

1. Cryptocurrencies
2. KBW Nasdaq Financial Technology Index
3. Dow Jones Global Technology Index

Comparator Group: The comparative group was not specifically defined in this study because its main goal was to apply quantile regression analysis theory to examine the correlation and co-movement of the study population.

Geographical Areas: This research integrates information from multiple geographic areas such as worldwide cryptocurrencies data, fintech indices and the Dow Jones global technology index. These variables guarantee a thorough and balanced examination of their co-movement across various locations.

Table 1
Source of the Data:

VARIABLE	MEASUREMENT	VARIABLE ADOPTION
	IN DEPENDENT VARIABLE	
KBW Nasdaq Financial Technology Index	Fintech Index	Abakah, E. J. A., Tiwari, A. K., Lee, C. C., & Ntow-Gyamfi, M. (2023). Quantile price convergence and spillover effects among Bitcoin, Fintech, and artificial intelligence stocks. International Review of Finance, 23(1), 187-205.
Dow Jones Global Technology Index	Global Technology Index	Erdaş, M. L., & Yağcılar, G. G. (2022). Bitcoin as An Investment Vehicle: The Asymmetric Relationships Between Bitcoin and Global Technology Indexes. Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 9(3), 2097-2120.
	DEPENDENT VARIABLE	
Cryptocurrencies	Bitcoin, Binance coin, Etherem, Ripple	Kumah, S. P., Odei-Mensah, J., & Baaba Amanamah, R. (2022). Co-movement of cryptocurrencies and African stock returns: A multiresolution analysis. Cogent Business & Management, 9(1), 2124595

Data was collected from these primary sources in this analysis:

a) Existing or Official Data: Investing.com provides historical data on cryptocurrencies and the Dow Jones global technology index. All of the research variables were covered by the data gathered from these reliable platforms.

b) Survey Data: The main goal of this study was to analyze the official and already existing dataset so for this no survey data was required.

Secondary Data

Secondary data analysis utilizes the use of information that has been gathered by another party. The sources of data for this study were Investing.com which provided historical data on KBW Nasdaq Fintech Indices, cryptocurrencies and other assets such as the Dow Jones Global Technology Index that was set for the previous five years. To get the necessary data for analysis we therefore needed to use the trustworthy sites.

After data collection, quantile regression analysis is performed to analysis the co-movement of cryptocurrencies, fintech indices and the Dow Jones global technology index. By using this method, we were able to break down time series data into its individual frequencies bands and find dimensional space correlations between them.

Statistical applications such as R studio and Python were used to analyze the data. After loading the data collected into the software, quantile on regression analysis was done to separate the data into different frequency bands. As the outcome the patterns, connections and movement of the variable's collectivity were carefully investigated.

On the other hand, secondary data analysis was thought to be the best method for this research. The study effectively found trends in the co-movement of cryptocurrencies, KBW Nasdaq Fintech Indices and the s&p Dow Jones Global Technology Index by using quantile on quantile regression analysis and data were found on investing.com and s&p global.com websites.

Data Download Sources

The dataset includes daily time series data for the cryptocurrencies, Fintech Index, Dow Jones Technology Index from January 2020 to December 2024. The information includes the time frame from January 1, 2020, to December 31, 2024. The websites s&p global.com and investing.com respectively provided information on indexes including the Fintech index and the Dow Jones Technology Index as well as cryptocurrencies like Bitcoin, Etherem, and Ripples. In order optimal comparison with returns all indices were converted to the natural logarithm as described in work of (Ahmed et al 2023).

The quantile-on-quantile Regression (QQR) Model

The Quantile-on-Quantile Regression (QQR) model was initially suggested by Sim and Zhou in 2015 and was developed by combining quantile regression (QR) and nonlinear techniques. Koenker and Bassett established the conceptual foundation for this model in 1978. The QQR models' flexibility allows it to leverage the dependencies that variables develop across various quantiles of their distributions, revealing more complex and asymmetrical relationships among them. The standard QR model focuses on the independent variables and their effects on the conditional distribution of dependent variables. A comprehensive examination of the intricate relationship between the variables of interest is made possible by this improved methodology.

The impact of cryptocurrencies distributions on the Fintech Index and the Dow Jones Technology Index at various quantiles is examined in this study using the non-parametric QQR Model. Through presenting significant observations regarding their underlying interactions, this investigation seeks to discover the intricate interaction between bitcoin values and the performance of major financial indices.

The quantile-on-quantile regression (QQR) model can be defined as follows.

$$ER_t = \beta^{\theta} (BITCOIN_t) + u_t{}^{\theta}$$
$$ER_t = \beta^{\theta} (BNB_t) + u_t{}^{\theta}$$
$$ER_t = \beta^{\theta} (ETH_t) + u_t{}^{\theta}$$
$$ER_t = \beta^{\theta} (XRPt) + u_t{}^{\theta}$$

Results and Discussion

Quantile Causality in Means Result and Quantile Regression Analysis

Analysis of quantile causality in means

We investigate and expand upon the categorical relationships among the Down Jones Technology index, Fintech Index and Cryptocurrencies for a variety of conditional distributions. Standard granger causality tests emphasize causal linkages at the mean level, whereas non-parametric quantile causality analysis examines causal relations throughout the quantile distribution. As it captures the causal relationships between the lowest, median and upper quantiles of the distributions it is useful to learn more about the direction of dependency between these variables.

Quantile Regression Analysis

The Quantile-on-Quantile Regression (QQR) offers a non-parametric approach to QR framed by Koenker and Bassett (1978) as proposed by Sim and Zhou (2015). The QQR technique captures connections throughout the whole distribution of both variables whereas QR enhances the traditional linear regression framework and focuses on the conditional effects of independent factors on the distribution of dependent variables. This refers to the relationship between regression coefficients and regression (Bossman et al., 2022 & Asafo-Adjei et al., 2022).

Equity market dynamics are classified into states ranging from optimistic and neutral to bearish in contrast to the extreme volatility and emotive emotions frequently observed in the cryptocurrency field. These intricate relationships cannot be represented by a single QR code or by conventional modeling methods like linear regression which is irrational. In order to address that gap we provided Quantile-on-Quantile Regression (QQR) on innovative use cases related to the KBW Nasdaq Fintech Index, the Dow Jones Global Technology Index and cryptocurrencies like Bitcoin (BTC), Binance Coin (BNB), Ethereum (Eth) and Ripple (XRP).

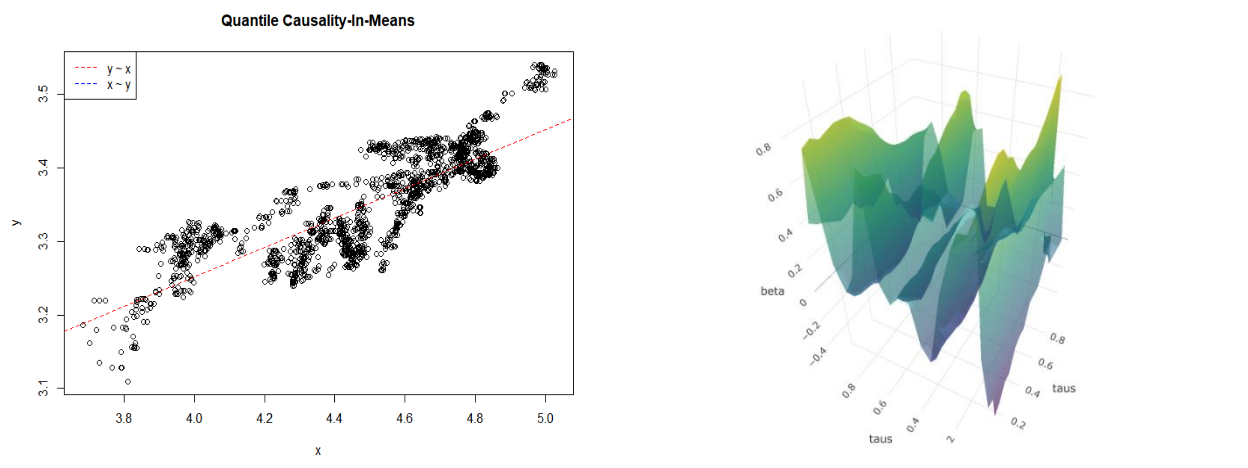
The QQR technique is used in this study to determine the impact of independent factors like KBW Nasdaq Fintech Index and Dow Jones Global Technology Index on the return distributions of dependent variables like Cryptocurrency. This model provides a solid foundation for understanding the dynamics between KBW Nasdaq Fintech Index, Global Technology Index and Cryptocurrencies since it captures the relationships between the organizations as they adjust to different market situations.

Table 2
Bitcoin vs KBW Nasdaq Financial Technology Index (BTC vs KNFTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	2.44804	0.02098	116.69889	0.00000
X	0.20085	0.00468	42.92642	0.00000

Figure 2
BTC vs KNFTI

BTC vs KNFTI



Bitcoin and the KBW Nasdaq Fintech Technology Index have a statistically significant positive relationship at the quantile 0.5 (median). An estimated median value of Bitcoin can be observed by the intercept value of 2.44804 when the KBW Fintech Index value is zero. The entire interception is highly statistically significant when $P<0.0001$ and t-value = 116.69889. The median value of Bitcoin increases with each unit increase in the KBW Fintech Index according to the slope coefficient of 0.20085. The findings are extremely statistically significant with p-values of 0.00000 for the slope and intercept coefficients. A linear upward trend in the price of Bitcoin appears to exist when compared to the KBW fintech index demonstrated by the red dashed line ("y ~ x") that fits well with the dense cluster of data points. The model fits well in the dark dotted clusters demonstrating the positive correlation.

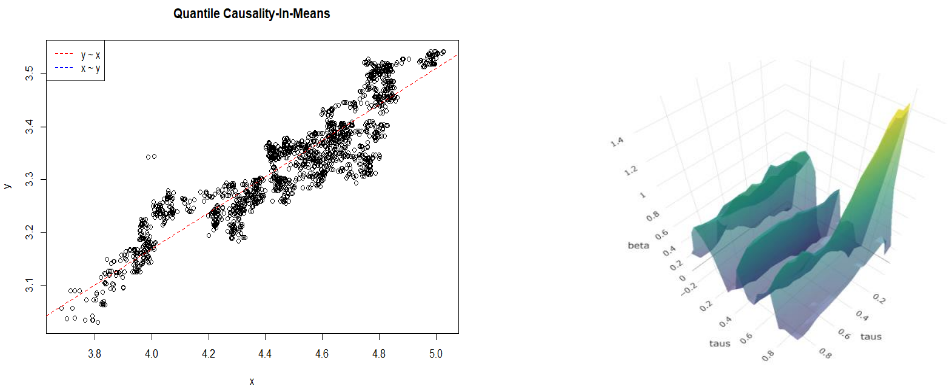
The asymmetric and nonlinear relationship between two financial variables across quantile is known as QQR analysis. This change is captured by the color gradient in the 3D surface plots where yellow green areas indicate strong positive correlation typically in bullish situations and deep blue areas indicate strong negative relationships generally in downturns or bearish market. Blur dominates in each of the sub plots for lower quantiles ($\tau < 0.2$) indicating that the outcome variable decreases as the independent variable rises supporting a decrease trend of overall market drops. On the other hand, yellow green peaks indicate a strong positive association at high quantile (beta = 0.8), meaning that bullish conditions boost financial profitability. A range of colors are reflected by the intermediate quantiles (τ = 0.4 to 0.6) indicating a weaker or somewhat favorable association during regular times. A strongly negative correlation is observed at the quantile of 25th, implying that Bitcoin has higher volatility and more downward pressure under a bearish fintech market. This connection is weakened to the 50th quantile, indicative of more staying power in neutral markets. Consider the fintech industry and let us test it with logarithm of bitcoin exchange rate; depends positively at the 75th quantile Bitcoin benefits from a prosperity of the fintech industry.

Table 3
BTC vs Dow Jones Global Technology Index (BTC vs DJGTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	1.80201	0.02062	87.40796	0.00000
X	0.34155	0.00460	74.27503	0.00000

Figure 3
BTC vs DJGTI

: BTC vs DJGTI



There is a statistically significant positive link between Bitcoin and the Dow Jones Global Technology Index at the quantile 0.5 (median). When the Dow Jones Global Technology Index is zero, the estimated median value of Bitcoin is reflected by the intercept value of 1.80201. At the t-value is 87.40796 and P<0.0001 the entire intercept is highly statistically significant. Both the slops and intercept coefficient have P-value of 0,00000, indicating that the results are highly statistically significant. The red dashed line ("y ~ x"), which matches effectively with the dense cluster of data points, shows that the price of Bitcoin appears to be on a linear increasing trend when compared to the Dow Jones Global Technology index. The dark dotted clusters showing the positive connection fit the model well.

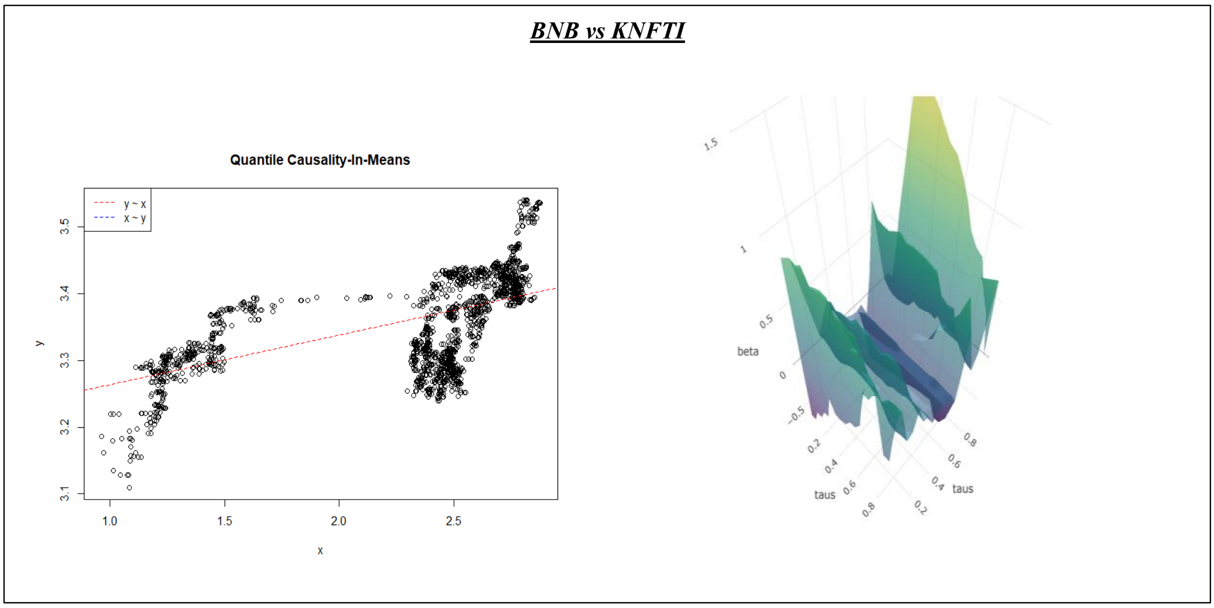
The variables nonlinear asymmetric and quantile dependent connection are shown in a 3D QQR model. The X-axis quantiles are an independent variable and Y-axis our beta coefficient at various quantile show the change in the correlation. Additional explanation is provided by the color gradient bright yellow peaks (beta= 1.4) indicate strong positive associations, green space (beta ≈ 0.8) indicates moderate relationships and dark blue areas (beta ≈ -0.5) indicate weak or negative relationships. The sharp rise in the beta value at the extreme quantile (0.9) in the table indicates that the effect is amplified for the higher quantiles. It suggests that the independent variable is more important at the extremes such as significant financial booms or economic crashes. The 25th quantity is less robust and also has small defensive properties for

Bitcoin during tech downturns. In reaction to adverse conditions at the 10th quantile, the comovement is quite high at both quantiles compared to periods of normal conditions this is less pronounced at the 50th quantile. Finally, the 75th quantile is also highly correlated positivel, and so we can consider that Bitcoin's price tends to follow technology during those bull runs. Since the lower and higher quantile do not appear to follow the same trends the asymmetry in the color distribution supports the QQR model.

Table 4
Binance Coin vs KBW Nasdaq Financial Technology Index (BNB vs KNFTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	3.18915	0.00599	532.21567	0.00000
X	0.07436	0.00255	29.16785	0.00000

Figure 4
BNB vs KNFTI



At the quantile 0.5 (median) there is a statistically significant positive correlation between KBW Nasdaq Fintech Index and BNB. When the Fintech Index value is zero the anticipated median value of BNB is reflected by the interceptive value of 3.18915. A T-value of 532.22 and a P-value of less than 0.0001 indicate that the entire interception is highly statistically significant. The slope coefficient of 0.07436 indicates that every unit increases in the KBW Financial Technology Index and the median value of BNB rises. The results are highly statistically significant with p-vales of 0.00000 for the slope and intercept coefficients. When compared to the KBW fintech index, the price of Binance coin appeared to be on a linearly growing trend, as seen by the red dashed line ("y ~ x"), which matches the dense cluster of data points effectively. The model was well fitted by the dark dotted at clusters indicating the

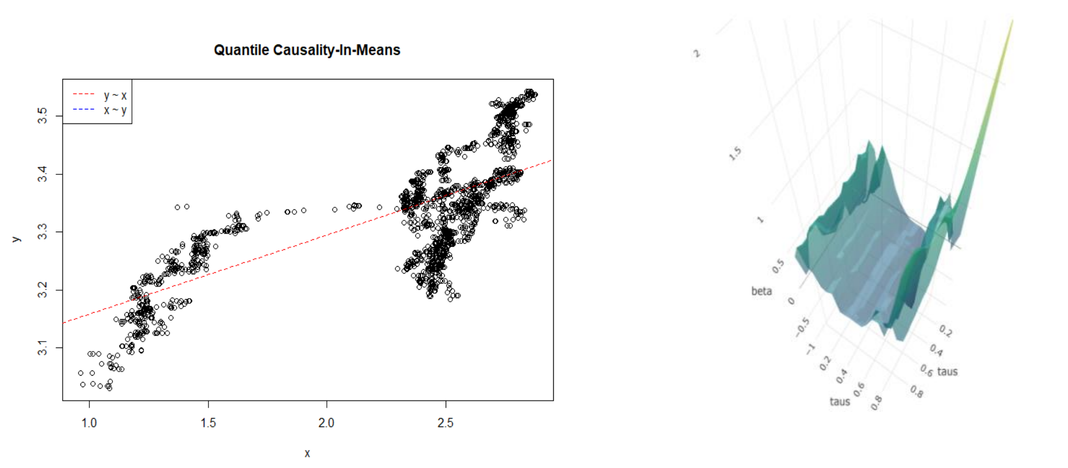
positive correlation and the light dotted at clusters indicating the less positive correlation on some points.
A 3D surface plot representation of the quantile-on-quantile regression QQR demonstrates an asymmetric nonlinear connection with larger moment's variation across quantiles. The independent and dependent variables are represented by the X and Y axis respectively and the strength of their association is shown by the Z axis beta values. As the color gradient suggests significant positive associations are indicated by green to yellow areas (beta =0.8 to 1.5) while weak or negative relationships are indicated by dark blue to purple areas (beta ≈ −0.5 to 0). Greater impacts in severe conditions are suggested by the plots which show stronger extreme quantiles greater than 0.8 effects when the beta reaches 1.5 yellow peaks. Asymmetry in the relationship is demonstrated by the lower quantile. The high degree of the sensitivity of BNB is evident in connection with the KNFTI at various quantiles. We find the relationship to be significantly negative around the 25th quantile, which means the Binance Coin responds strongly to adversity in the fintech sector. The link spreads out in 50th quantile, implying it becomes more independent in normal market. Details across quantiles the 75th percentile shows little overlap. It proves the positive correlations of QQR model variables.

Table 5
Binance Coin vs. Dow Jones Global Technology Index (BNB vs DJGTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	3.02145	0.00597	506.19993	0.00000
X	0.13651	0.00254	53.75499	0.00000

Figure 5
BNB vs DJGTI

Figure 4: BNB vs DJGTI



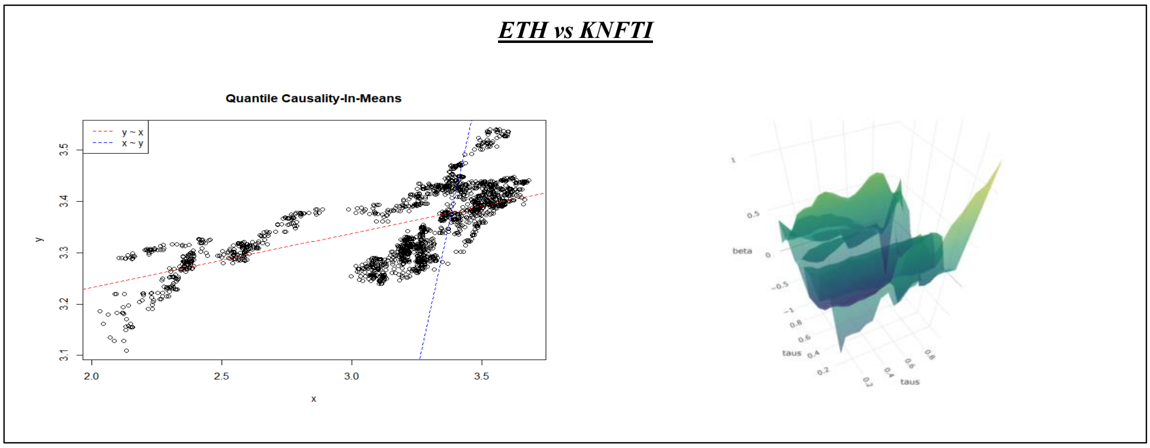
There is a statistically significant positive association between BNB and Dow Jones Global Technology Index at the quantile 0.5 (median). When the Dow Jones Global Technology Index is equal to zero the intercept value of 3.02145 indicates and expected median value of BNB. A T-value of 506.19 and a P-value of less than 0.0001 indicate that the entire intercept is highly statistically significant. The median value of BNB increases with each unit increase in the Dow Jones Global Technology Index according to the slope coefficient of 0.13651. The findings are extremely statistically significant with p-values of 0.00000 for the slope and intercept coefficients. The upward sloping red regression line indicated a favorable causal link between x and y. The red line is closely followed by the dark dots which represent high density sparsely of sites and the lights dots which represented low density areas or more scattered this is suggesting less positive or nonlinear relationship that could be caused by the unnoticed factors or market anomalies.

An asymmetric nonlinear relationship with higher moment's variation across quantile is shown by a 3D surface plot depiction of the quantile-on-quantile regression QQR. The Z axis beta values indicate the degree of correlation between the independent and dependent variables, which are represented by the X and Y axes, respectively. According to the color gradient, dark blue to purple areas (beta ≈ −0.5 to 0) indicate weak or negative links, whereas green to yellow areas (beta = 0.5 to 2) indicate significant positive associations. Plots that display stronger extreme quantiles larger than 0.8 effects when beta approaches 2 yellow peaks represent bigger impacts under severe situations. The lower quantile illustrates the asymmetry in the relationship. In bearish markets, BNB's dependence on DJGTI is relatively weak 25th quantile, although we observe a modest positive co-movement at the 50th quantile and stronger correlation at the 75th quantile. This indicates that Binance Coin is more responsive to positive developments in the tech realm.

Table 6
Etherem vs KBW Nasdaq Financial Technology Index (ETH vs KNFTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	3.01874	0.01012	298.37074	0.00000
X	0.10636	0.00317	33.58414	0.00000

Figure 6
ETH vs KNFTI



An Eth-KBW Nasdaq Fintech Index positive association is statistically significant at the quantile 0.5 (median). The predicted median value of Eth when the KBW Fintech Index value is zero is reflected by the interceptive value of 3.1874. A t-value of 298.37 and P-value of less than 0.0001 indicate that the entire interception is highly statistically significant. The median value of ETH increases with each unit increase in the Fintech Index according to the slope coefficient of 0.10636. Both the slope and intercept coefficients have p-value of 0.00000 indicating that the results are highly statistically significant. A general upward trend in the value of Etherem given an increasing KBW Fintech index is indicated by the red dotted line ("y ~ x") which fits well with the high-density cluster data points. The blue dashed line ("x ~ y") indicates that x may induce changes in y since it regresses x on y. The teal points that are most tightly packed correspond well with the positive relationship concept. A 3D QQR model demonstrates the quantile dependent and nonlinear asymmetric relationship between the variables. Our beta coefficient at different quantiles on the Y-axis indicates the change in the correlation, while the quantiles on the X-axis represent an independent variable. The color gradient offers further explanation strong positive associations are indicated by bright yellow peaks (beta = 1.0), moderate relationships are indicated by green space (beta ≈ 0.5), and weak or negative relationships are indicated by dark blue areas (beta ≈ -0.5). The table's extreme quantile (0.4) shows a sharp increase in the beta value, indicating that the effect is amplified for the higher quantiles. It implies that at extremes such notable financial booms or economic disasters, the independent variable is more significant. Ethereum's 25th quantile is large and negative which implies that Ethereum shows a dramatic and significant negative response to sectoral stress in fintech, thus subjecting ETH to the overall market pessimism experienced in the fintech sector. Although at the 75th quantile reveals minor co-movement with fintech growth, at the 50th quantile it exhibits a positive or neutral relationship.

Table 7

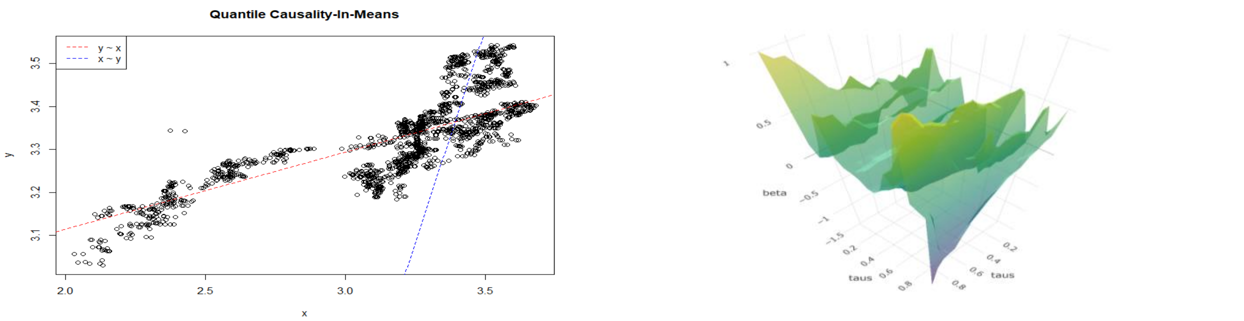
Etherem vs Dow Jones Global Technology Index (ETH vs DJGTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	2.75627	0.01396	197.41301	0.00000
X	0.17903	0.00437	40.96214	0.00000

Figure 7

ETH vs DJGTI

Figure 6: ETH vs DJGTI



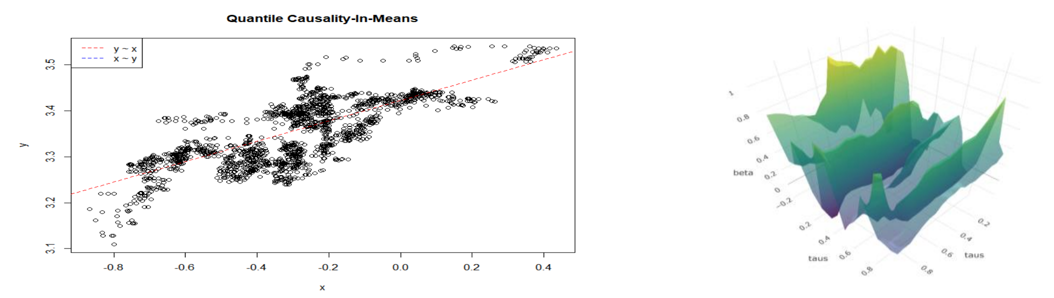
At the quantile 0.5 (median) there is a statistically significant positive association between ETH and Dow Jones Global Technology Index. When the Dow Jones Global Technology Index value is zero the intercept value of 2.75627 indicates an estimated median value of Etherem. A t-value of 197.41301 and a P-value of less than 0.0001 indicate that the entire intercept is highly statistically significant. The media value of Etherem increases with each unit increase in the Dow Jones Global Technology Index according to the slope coefficient of 0.17903. The findings are extremely statistically significant with p-values of 0.00000 for the slope and intercept coefficients. A general upward trend in the value of Etherem given an increasing Dow Jones Global Technology index is indicated by the red dotted line ("y ~ x") which fits well with the high-density cluster data points. The blue dashed line ("x ~ y") indicates that x may induce changes in y since it regresses x on y. Darker clusters highlight regions where most of the data is concentrated. Light dots or sparse areas indicate less common or extreme values in the dataset. A 3D QQR model demonstrates the quantile dependent and nonlinear asymmetric relationship between the variables. The Y-axis displays the change in the correlation, while the X-axis quantiles represent an independent variable. A further explanation is given by the color gradient, where dark blue areas (beta ≈ 0.8) indicate weak or negative relationships, green space (beta ≈ 0.4 to 0.5) indicates moderate relationships, and bright yellow peaks (beta = 1.0) indicate strong positive associations. The table's extreme quantile (0.5) shows a sharp increase in the beta value, indicating that the effect is amplified for the higher quantiles.

Table 8
Ripple vs KBW Nasdaq Financial Technology Index (XRP vs KNFTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	3.42260	0.00209	1641.31110	0.00000
X	0.22221	0.00543	40.90689	0.00000

Figure 8
XRP vs KNFTI

Figure 7: XRP vs KNFTI



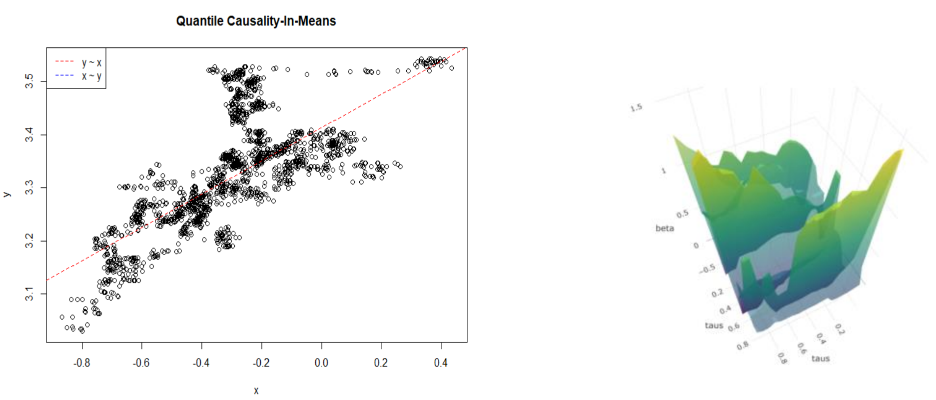
There is a statistically significant positive association between XRP and the KBW Nasdaq Fintech Index at the quantile 0.5 (median). When the Fintech Index value is zero, the interceptive value of 3.42260 indicated an estimated median value of XRP. A t-value of 1641.311 and a P-value of less than 0.0001 indicate that the entire intercept is highly statistically significant. The median value of XRP increases with each unit increase in the Fintech Index according to the slope coefficient of 0.22221. The findings are extremely statistically significant with a p-value of 0.00000 for the slope and intercept coefficients. The red dashed line ("y ~ x") indicates a positive relationship y is expected to increase as x does. In the areas of high observation density, the model faithfully captured the data as shown by the density of black dots surrounding the red line. Lower observation density and relative variations from the model's prediction along with non-linear dynamics are indicated by the light dots in the light's edges. The quantile dependent and nonlinear asymmetric relationship between the variables is illustrated by a 3D QQR model. The quantiles on the X-axis represent an independent variable, and our beta coefficient at various Y-axis quantiles shows the change in the correlation. The color gradient provides further context by showing that bright yellow peaks (beta = 1.0) represent strong positive links, green space (beta ≈ 0.4) indicates moderate relationships, and dark blue areas (beta ≈ -0.5) suggest weak or negative relationships. The effect is magnified for the higher quantiles, as evidenced by the substantial increase in the beta value at the table's extreme quantile (0.4). KNFTI are negatively related to XRP, as documented by its weak or negative exposure at the 25th quantile.

Table 9
Ripple vs Dow Jones Global Technology Index (XRP vs DJGTI)

Call: rq (formula = y ~ x, tau = tau)				
tau: [1] 0.5				
Coefficients:				
	Value	Std.	Error t value	Pr(>|t|)
(Intercept)	3.41312	0.00268	1273.09367	0.00000
X	0.31297	0.00698	44.81358	0.00000

Figure 9
XRP vs DJGTI

Figure 8: XRP vs DJGTI



There is a statistically significant positive association between XRP and the Dow Jones Global Technology Index at the quantile 0.5 (median). An anticipated median value of XRP when the Dow Jones Global Technology Index value is zero is indicated by the intercept value of 3.41312. Any intercept that has a t-value of 1273.093 and a P-value of less than 0.0001 is highly statistically significant. According to the slope coefficient of 0.31297 the median value of XRP increases for each unit increase in the Dow Jones Global Technology Index. Both the slope and intercept coefficients have p-values of 0.00000 indicating that the results are highly statistically significant. A positive relationship is indicated by the red dashed line ("y ~ x"), which means that y should rise as x does. The density of black dots surrounding the red line indicates how well the model represented the data in the regions with high observation densities. The light dots at the light's borders show non-linear dynamics, lower observation density, and relative deviations from the model's prediction, while there are differences in the spatial fill of the dots in the intervals of x, the remaining intervals do not deviate much from this pattern.

A 3D QQR model demonstrates the nonlinear asymmetric and quantile dependent interaction between the variables. Our beta coefficient at different Y-axis quantiles illustrates the shift in the correlation, while the quantiles on the X-axis reflect an independent variable. By demonstrating that strong positive ties are represented by bright yellow peaks (beta = 1.5), moderate relationships are shown by green space (beta ≈ 0.5 to 1.0), and weak or negative relationships are suggested by dark blue areas (beta ≈ 0.6 to 0.2), the color gradient adds even more detail. The significant increase in the beta value at the extreme quantile (0.54) of the table indicates that the effect is amplified for higher quantiles. In the 25th, 50th and 75th quantiles, the relationship of XRP with DJGTI is milder and slightly positive, signifying a less strong linkage with the collective emotion of tech sector. Since the lower and higher quantile do not appear to follow the same trends the asymmetry in the color distribution supports the QQR model.

Quantile Causality in Means Analysis

The results represent the findings of the daily quantile-based causality in means test on the financial indices under research. Each panel displays test statistics on the vertical axis and quantile on the horizontal axis to illustrate these test statistics. A solid horizontal reference lines that indicate a P-value of 0.00 and a 5% significance level. The causality in means line being below the P-values reflects the null hypothesis which holds that fluctuation in fintech index and cryptocurrency prices do not cause the granger movements in Dow Jones Global Technology Index.

This means that a unit increase in the fintech index or Dow jones Global Technology index levels cause changes in the median value of the dependent variable cryptocurrency since the coefficient of the independent variables is statistically significant. This analysis uses the quantile causality in means to outline the transmission functions of fintech index, Dow jones Global Technology index and cryptocurrencies such as Bitcoin, Etherem, Binance coin and Ripple. The study evaluates how independent variables predict dependent variables at various quantiles by using the quantile meaning in line with earlier research (Agyei 2022; Alsubaie et al., 2022; Umar et al., 2023). The results are presented both numerically and graphically with the critical value for a 95% confidence interval (5% significance level) shown by the bold horizontal line.

Quantile-on-Quantile Regression Analysis

This section uses the Quantile Regression (QR) technique to investigate the relationship between the four cryptocurrencies of interest like BTC, ETH, BNB and XRP and two significant financial metrics, the KBW Financial Technology Index and the Dow Jones Technology Index. The results presented demonstrate the impact of those independent factors on the bitcoin return across various quantiles. The research results indicate that cryptocurrencies and the indices at lower and upper quantiles have both positive and weak or less positive quantile relationships.

The study revealed further notable trends with cryptocurrencies showing inverse responses to fintech and global technology index movements during bearish conditions and direct correlation during bullish phases. These results indicate that economic indicators such as the Dow Jones Global technology index could be considered potential hedging instruments for cryptocurrency investments in economic collapse periods. The study's mixed results are in line with other research by Bossman, et al. (2023), Bedowska-Sojka et al. (2022), and Umar et al. (2022) which highlights the complex and varied relationships between financial indices and cryptocurrencies.

On the other hand, QR indicates that the correlation between cryptocurrencies and the KBW Fintech Index and Dow jones Global Technology Index is strong despite of the market's attitudes be it optimistic, negative or neutral. A significant dependency on bullish market conditions becomes apparent when the correlation expands and turns positive at higher quantiles.

The findings also build on earlier research by Liu et al. (2013), highlighting the importance of cryptocurrency investors paying attention to the movements of significant equity like KBW Fintech Index and Dow jones Global Technology Index because of their interconnected market dynamics. This analysis confirms that rising financial market volatility can materially affect cryptocurrency returns as mentioned by Fan Xu et al. (2023). The testing results of the interconnections of different asset classes were further supported by Shakri's (2021) discovery that rising volatility has an adverse effect on market returns.

Table 10
Hypothesis Summary

	Assessment Summary	
H1	Significant relationship between KBW Nasdaq Financial Technology Index and cryptocurrency prices	**Accepted**
H2	Significant correlation between currency pairs and Dow Jones Global Technology Index	**Accepted**
H3	Co-movement and Correlation of crypto-currencies, KBW Nasdaq Fintech Index and Dow Jones Global Technology Index can be effectively decomposed and analyzed using the Quantile-on-Quantile Regression Analysis	**Accepted**

Conclusion and Discussion

This empirical study is using causality in means and Quantile-on-Quantile Regression (QQR) methodology to investigate the asymmetric effects of cryptocurrencies like Bitcoin, Binance coin, Etherem and Ripple on the Fintech Index and the Dow Jones Technology Index using time series analysis. Our findings verify the theory by providing important empirical evidence of the asymmetric effects of these cryptocurrerncies on financial indices at extreme quantiles of bullish and bearish markets. These results align with the important findings made by Bedowska-Sojka et al. (2022), Salisu et al. (2022) and Umar et al. (2022) that show the quantile specific impact caused by cryptocurrencies over different financial asset groups.

This study shows that there are differences in the strength and direction of the impact of Bitcoin, Binanace Coin, Etherem and Ripple on the developed indices such as the KBW Financial Technology Index and Dow Jones Global Technology Index. According to our research exposure to these indexes is comparatively stable considering the volatility of cryptocurrencies which makes them useful for reducing risk in the digital asset market. The dynamic interactions show that the sensitivity of financial indices to cryptocurrencies is highest in extreme market conditions and approaches zero in stable or normal states.

It is recommended that stock market investors monitor changes in cryptocurrency prices particularly those of Bitcoin, Binance Coin, Etherem and Ripple as this may allow them to modify portfolio allocations and enhance diversity. Additionally, there is a noticeable decline in the dependency of financial indices on these assets when the market is steady and the cryptocurrencies are in the intermediate quantiles. The results might help authorities in implementing measures to reduce systemic risks and maintain financial stability by maintaining cryptocurrency prices within these consistent ranges.

This analysis provides significant information about the relationship between cryptocurrencies and the main financial indices. Therefore, it helps the community of portfolio managers make decisions regarding investments and policymakers regulate financial trends by providing a thorough understanding of the asymmetric effects of the underlying assets in the cryptocurrency market on the financial markets of highly volatile developed economies.

Limitation and Future Research

There are some limitations although this study provides a useful idea of the asymmetric and nonlinear relationship in relation to the fintech and technology stock indices and the dynamics of cryptocurrencies. To begin with, the analysis is based on just a small number of variables: four leading cryptocurrencies (Bitcoin, Ethereum, Binance Coin, and Ripple) and two financial indices (KBW Nasdaq Financial Technology Index and Dow Jones Global Technology Index). This focus had a good point, yet such tool offers a limited perspective, which may not accurately reflect on what other new digital token or index including focal specialized DeFi or fintech, may act. Second, incorporating monthly information from 01st January 2020 to 31st December 2024 might fail to capture high frequency market incidences and short-term market movements, in the case of sudden shift in investor sentiment or macroeconomic shocks. Third, the global focus of this study did not allow distinctions to be made on the basis of differences in regional regulatory institutions and in the level of digital financial development.

A number of extensions could be adopted for future use. Above daily or hourly data, researchers might need to use daily data in order to better understand high frequency relationships between cryptocurrencies and financial benchmarks. The methodology could also potentially be expanded to include industry specific stock benchmarks or regional fintech indexes, particularly those in emerging markets such as GCC or South Asia where fintech and cryptocurrency usage is rapidly growing. In addition to that the introduction of tokenized assets, DeFi indices, or AI-driven fintech indicators may reveal new dynamics that are overlooked by traditional stock indices. Lastly, to accommodate the temporal dynamics and structural breaks in crypto-financial interactions, other techniques, such Wavelet-based QQR, panel QQR, or ML-powered QQR may be explored by future research.

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