A Comparative Analysis of the Effect of Liquidity on the Price of Bitcoin by Rushil Jaiswal

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Abstract

This paper delves into the intricate relationship between liquidity indicators and the price dynamics of Bitcoin, a prominent cryptocurrency. Liquidity, a fundamental aspect of financial markets, profoundly influences market stability and efficiency. Leveraging statistical analysis and AI modeling techniques, my study explores various liquidity metrics—including trading volume, bid-ask spread, volatility, number of transactions, and bid and ask sums as separate indicators—to assess their impact on the price of Bitcoin. The findings offer valuable insights into the factors driving Bitcoin price movements and shed light on the role of liquidity in cryptocurrency markets. Through correlation analysis as well as three different machine learning models – random forests, XGBoost, and linear regression – , my study evaluates the significance of individual liquidity factors and their relationships with Bitcoin prices. The best performing model was the random forest regressor and XGBoost where I identified that the volatility was the feature that was the most informative of the model's performance. My research contributes to advancing our understanding of liquidity and price discovery in cryptocurrency markets and underscores the need for future studies to explore alternative factors and mechanisms shaping cryptocurrency prices. By embracing the findings and continuously refining analytical approaches, researchers can navigate the evolving landscape of cryptocurrency trading, ultimately enhancing market efficiency and informing regulatory decisions.

Keywords: Bitcoin, Liquidity Indicators, Trading Volume, Bid-Ask Spread, Price Dynamics, Cryptocurrency Markets,Volatility, Trading, Number of Transactions.

I. Introduction

In the dynamic realm of cryptocurrency markets, the interaction between liquidity and price movements is a pivotal focus for researchers, traders, and investors alike. As a developing and widely traded digital asset, Bitcoin has garnered increasing attention for its inherent volatility, characterized by abrupt price fluctuations.

Bitcoin (BTC), developed by Satoshi Nakamoto in 2009, is a decentralized cryptocurrency underpinned by blockchain technology (Investopedia). Unlike purchasing stock in a company, which grants ownership in the company itself, buying Bitcoin provides ownership of the cryptocurrency based on the amount purchased. Bitcoin's price is primarily influenced by supply and market demand; however, there are additional factors that are often overlooked. The volatility and market liquidity of Bitcoin, as well as other liquidity indicators such as trading volume and bid-ask spreads, also play significant roles in determining its price dynamics. This research aims to explore these lesser-considered factors to gain a more comprehensive understanding of the forces driving Bitcoin's market value.

Understanding the relationship between liquidity and price changes is essential for grasping the intricacies of the cryptocurrency market and developing informed strategies for navigating its complexities.This paper embarks on a comprehensive comparative analysis, aiming to dissect and evaluate the influence of liquidity on the price dynamics of bitcoin. Liquidity, a multifaceted concept, encompasses the ease with which an asset can be bought or sold in the market without causing significant price disruptions (Bitcoin.com, Investopedia). This research addresses two fundamental questions surrounding the liquidity-pricing relationship in the Bitcoin market: [1] Do liquidity metrics accurately capture the market dynamics? [2] Are there discernible patterns in the market impact of large trades concerning liquidity fluctuations?. This comparative approach allows us to juxtapose different market conditions, timeframes, or liquidity rules, offering a nuanced understanding of how liquidity dynamics may vary and impact Bitcoin's price behavior. To carry out these comparisons, correlation analysis as well as three types of machine learning models – random forests, XGBoost, and linear regression – are applied. The model with the best performance was the Random Forest and XGBoost with R^2 = 0.91 Furthermore, I also applied feature analysis to understand the most important factors driving the models' predictions. Here, we find that for the highest performing model, the feature that is most influential is the volatility.

This research is pivotal in advancing our understanding of how liquidity metrics impact Bitcoin's price dynamics. While much of the existing literature has focused on traditional financial assets, this study highlights how specific liquidity indicators- such as bid-ask spread, trading volume, and volatility, bid prices, and ask prices - affect Bitcoin, a unique, and highly volatile cryptocurrency. By integrating high frequency and low frequency liquidity measures, the study fills a critical gap in the literature by providing a more nuanced analysis of how these factors influence Bitcoin price.The findings offer valuable insights for investors and traders seeking to navigate the complexities of cryptocurrency markets, and they can also guide policymakers in developing informed regulations that address the unique challenges and risks associated with digital currencies.

Cryptocurrency research has surged, with many studies exploring the intricate relationship between Bitcoin price dynamics and liquidity. Due to Bitcoin's volatility, decentralized nature, and global reach, understanding liquidity's impact on price fluctuations is crucial.

Early studies by Kyle (1985) and Amihud et al. (1986) laid the groundwork for understanding liquidity through bid-ask spreads and trading volume. Theoretical frameworks from market microstructure studies by O'Hara (1995) and Madhavan (2000) further dissected liquidity and price dynamics. Recent research by Yelowitz (2015) examines the market microstructure of cryptocurrency exchanges, highlighting nuances in liquidity provision and price impact.

Abdi and Ranaldo (2017) found low-frequency transactions-based liquidity measures to be effective compared to high-frequency benchmarks. Their study highlights the performance of various liquidity estimators, including the Corwin and Schultz (2012) estimator, in describing time-series variations across different observation frequencies, trading venues, and cryptocurrencies.

Building on this literature, this paper analyzes the impact of liquidity on Bitcoin's price changes, comparing high-frequency liquidity measures with low-frequency measures for Bitcoin (BTC). This investigation reveals that low-frequency liquidity measures provide accurate liquidity estimates in cryptocurrency markets incorporating new empirical evidence.

II. Methods

A. Data

The data for analysis was sourced from data.bitcoinity.org. It encompasses price data and changes in Bitcoin price over the past five years, along with metrics pertaining to the selected liquidity indicators for the same duration. This dataset was deemed suitable for the research, providing a comprehensive foundation for examining the relationship between liquidity factors and Bitcoin prices over time. This research employs a meticulous methodology and leverages relevant data sources to illuminate the intricate interplay between liquidity dynamics and Bitcoin price movements, offering valuable insights for market participants and researchers alike.

With respect to issues with the data, missing data was addressed by removing data for all the other features, making sure we only keep the data for the parts where all the information is there. In addition, the price of bitcoin and liquidity indicators was log-transformed. We found that transforming the data in this manner yielded better empirical results and amplified the signal present in the data.

B. Feature Selection

After a review of the literature, a set of liquidity indicators was chosen to proceed with the analysis. These indicators were selected based on their perceived ability to effectively reflect the liquidity dynamics within the Bitcoin market. The chosen liquidity indicators include:

Bid-Ask Spread: This metric signifies the difference between the highest price a buyer is willing to pay (bid) and the lowest price a seller is willing to accept (ask). A narrower spread typically indicates higher liquidity.

Number of Bids: This metric represents the total volume of bids within the market. It provides insight into the demand side of the market and the level of interest from buyers.

Number of Asks: This metric represents the total volume of asks within the market. It provides insight into the supply side of the market and the level of interest from sellers.

Volatility: Volatility measures the degree of variation in Bitcoin's price over a certain period. High volatility may indicate lower liquidity as it can deter market participants due to increased risk.

Trades Per Minute: This metric quantifies the frequency of trades occurring within a minute. A higher number of trades per minute may suggest higher liquidity as it reflects active participation in the market.

Trading Volume: Trading volume represents the total number of Bitcoin units traded within a specified period. Higher trading volume generally indicates higher liquidity.

Number of Transactions: This metric counts the total number of transactions executed on the Bitcoin network within a given timeframe. It offers insights into the activity level and participation in the Bitcoin ecosystem.

C. Statistical and Machine Learning Methods

The main graphs I used to analyze my results compared the liquidity factors to the price of Bitcoin to understand their correlation. Lastly, I created AI models using XGBoost, Linear regression, and Random Forest Regression and calculated the R-squared values for each model to evaluate their performance.

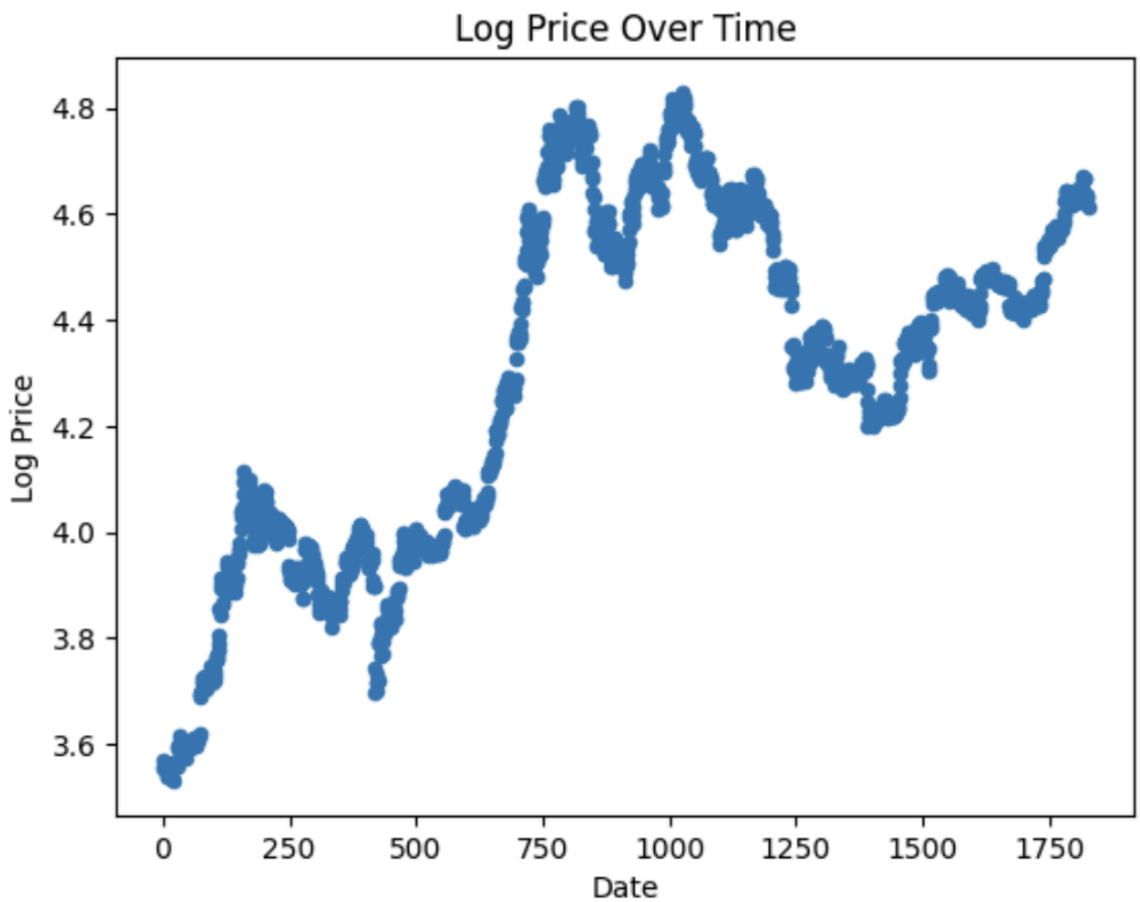

Figure 1:
The log price change of Bitcoin over the years from around 2019 to present date.

Figure 2:
The log volatility change of Bitcoin affected its price over the years, from around 2019 to the present date.

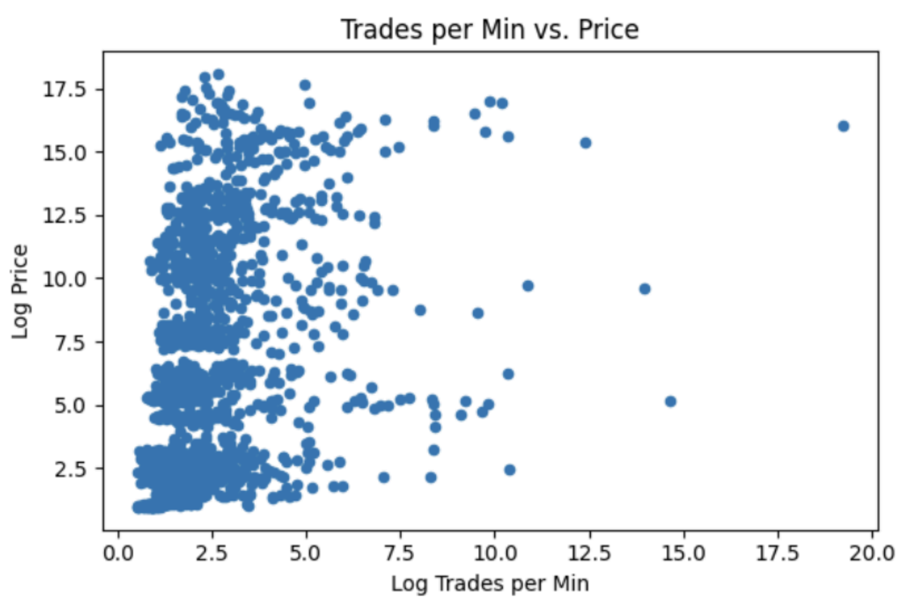

Figure 3:
The log transactions change of Bitcoin affect on the price of Bitcoin over the years from around 2019 to the present date.

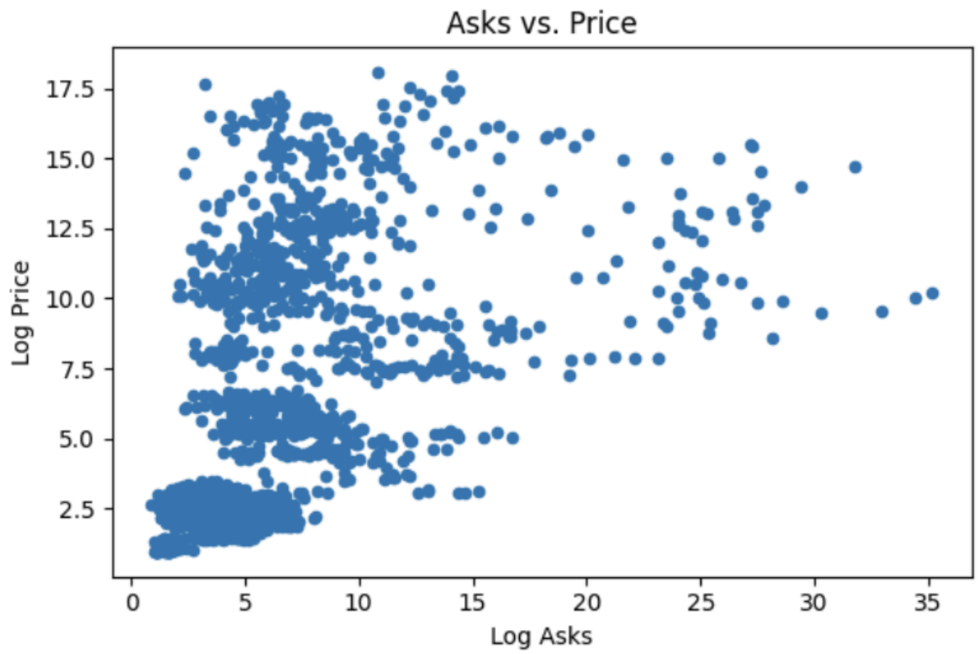

Figure 4:
The log asks change of Bitcoin affects the price of Bitcoin over the years from around 2019 to the present date.

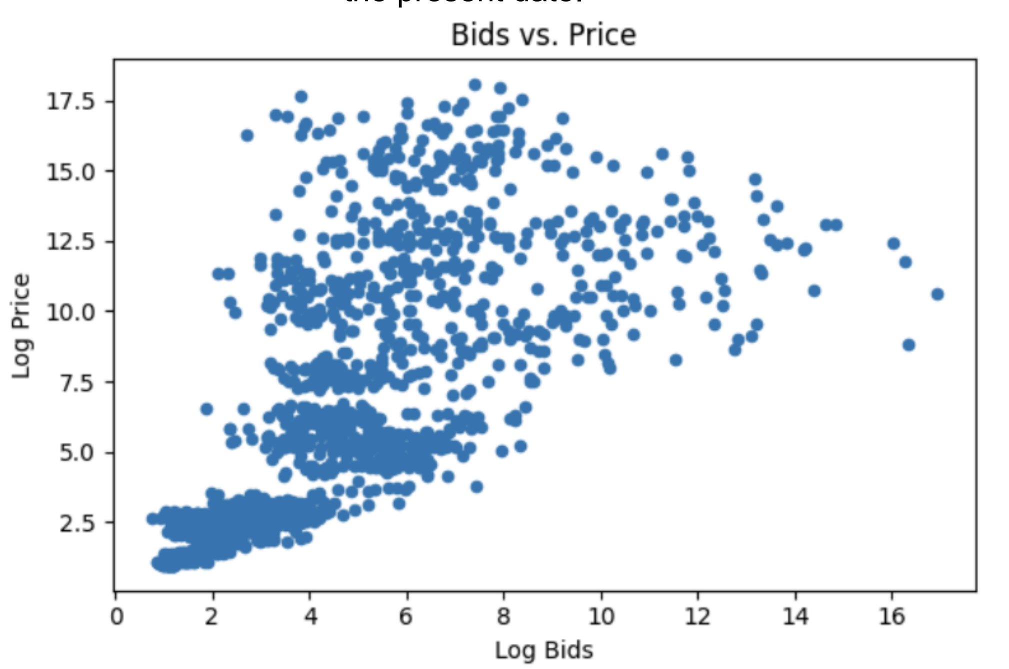

Figure 5:
The log bids change of Bitcoin affects the price of Bitcoin over the years from around 2019 to the present date.

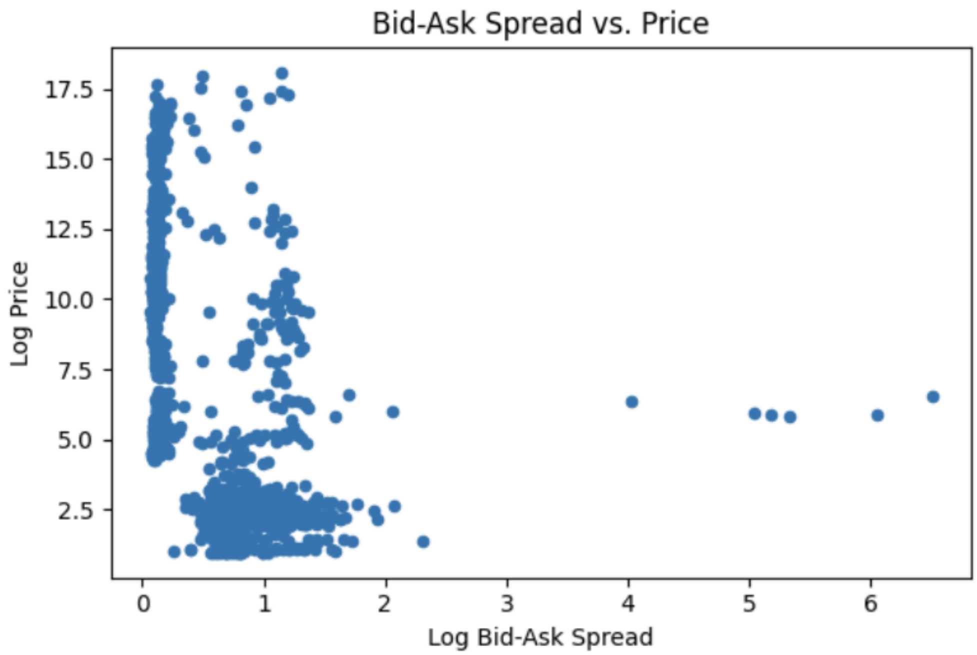

Figure 6:
The Log Bid-Ask Spread change of Bitcoin affects the price of Bitcoin over the years from around 2019 to the present date.

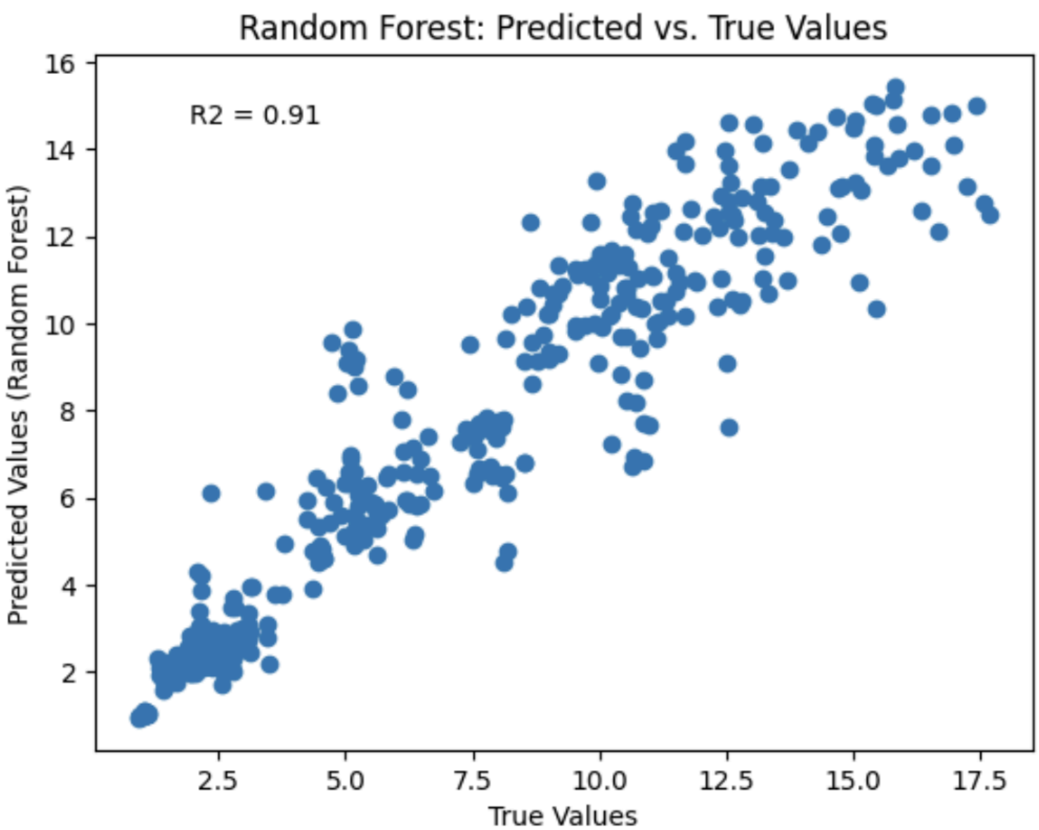

Figure 7:
The Predicted and True R2 Values for the Random Forest Model

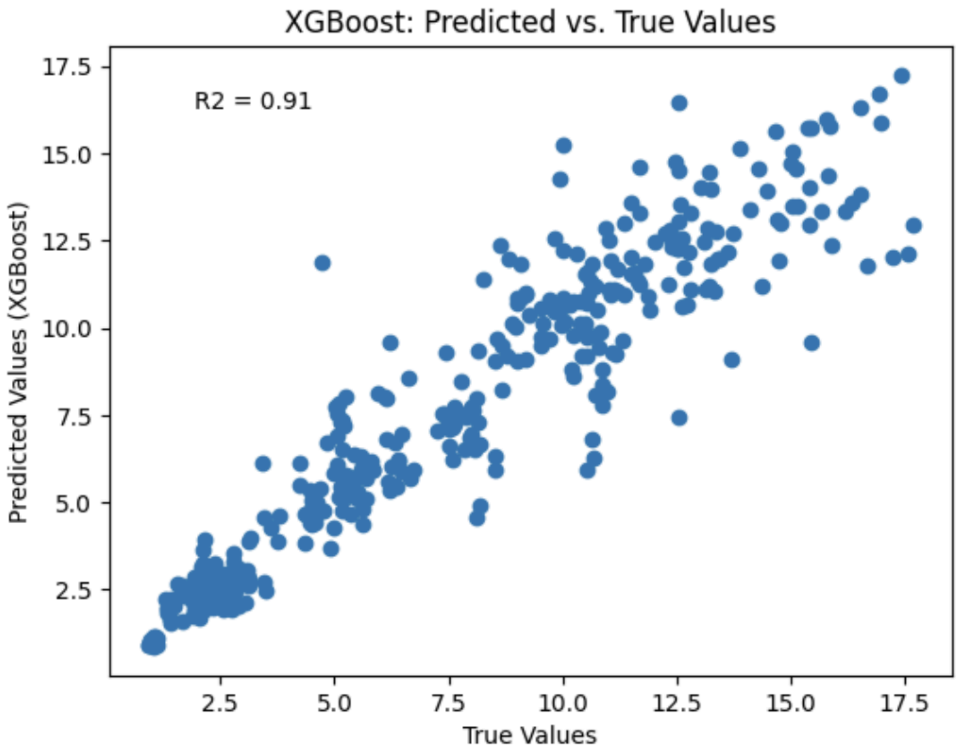

Figure 8:
The Predicted and True R2 Values for the XGBoost Model

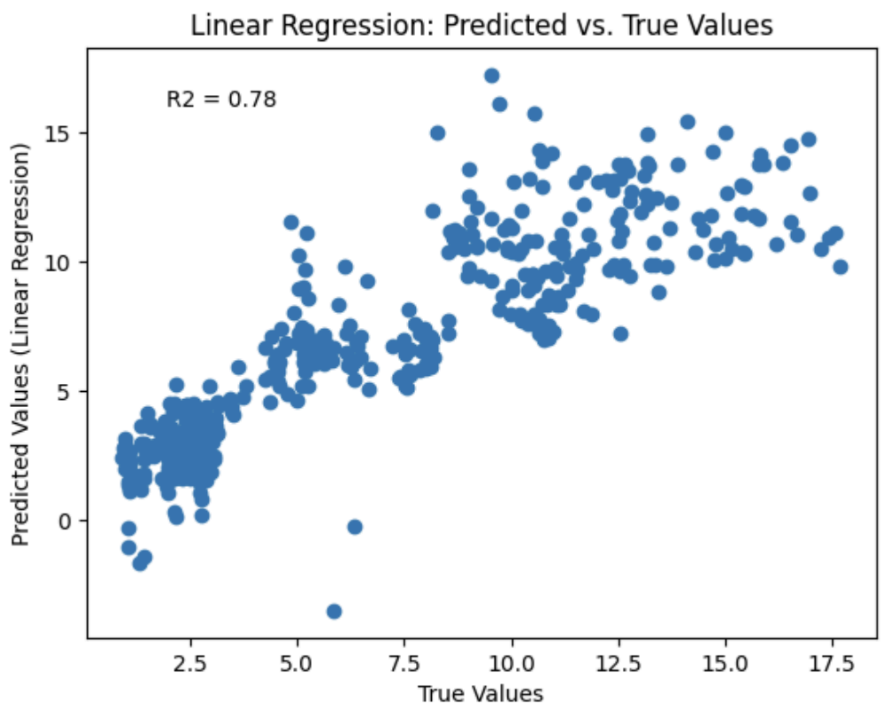

Figure 9:
The Predicted and True R2 Values for the Linear Regression Model

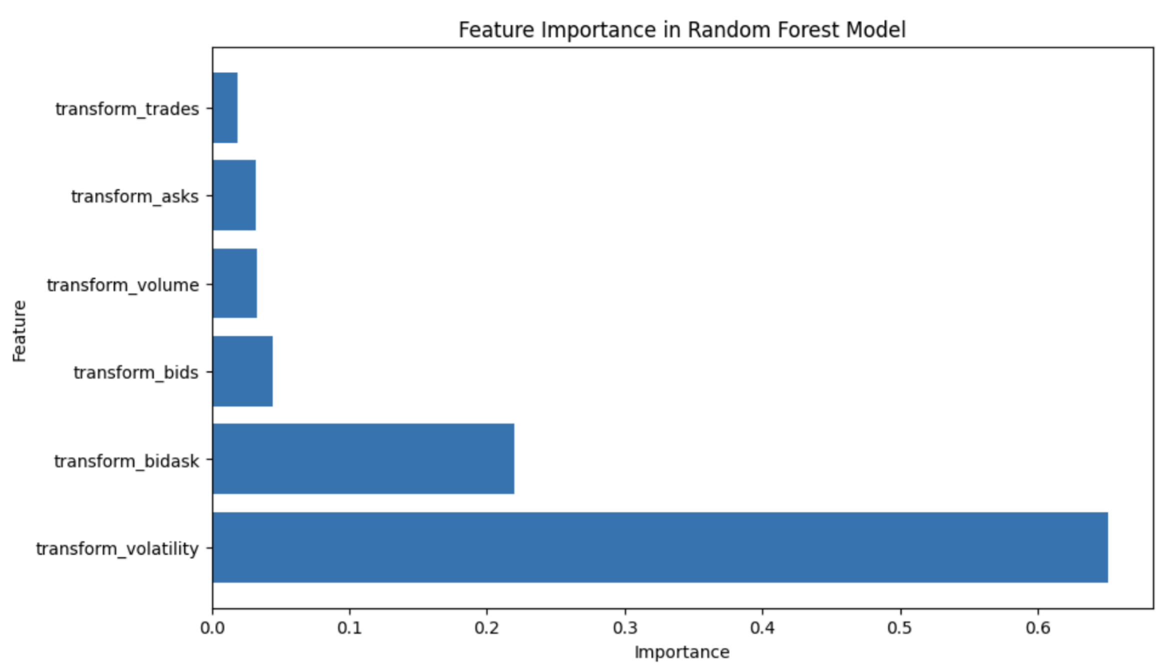

Figure 10:
Feature Importance in the Random Forest Model

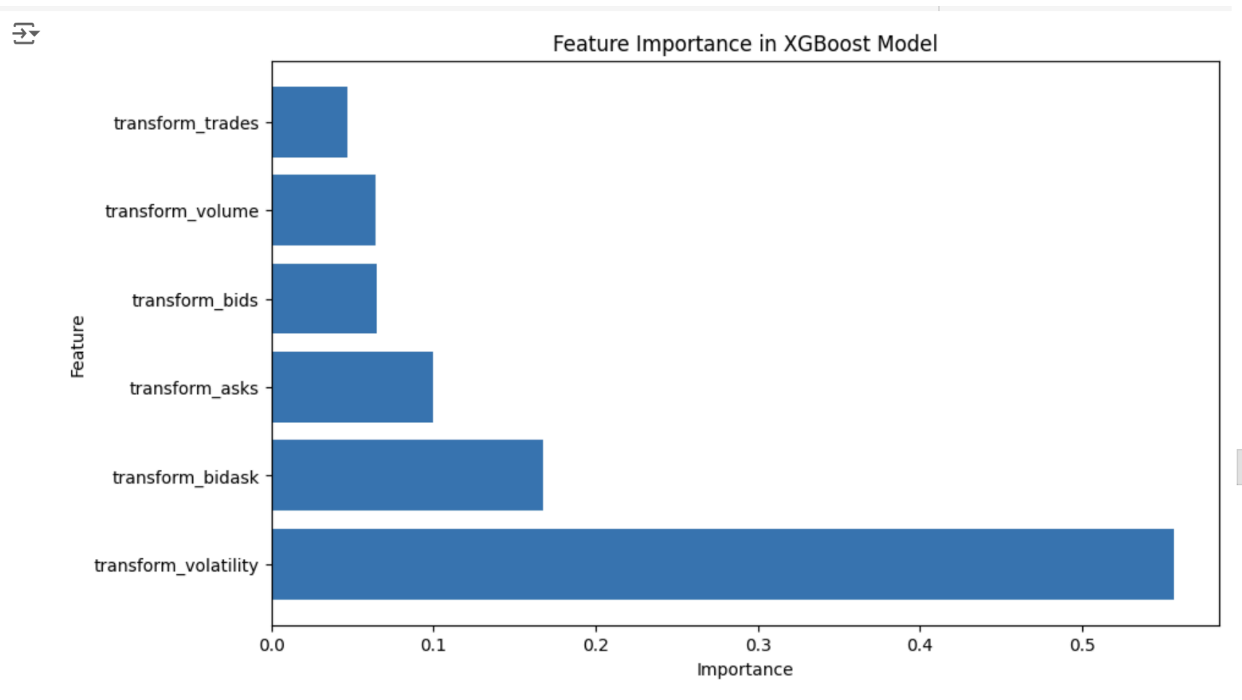

Figure 11:
Feature Importance in XGBoost Model

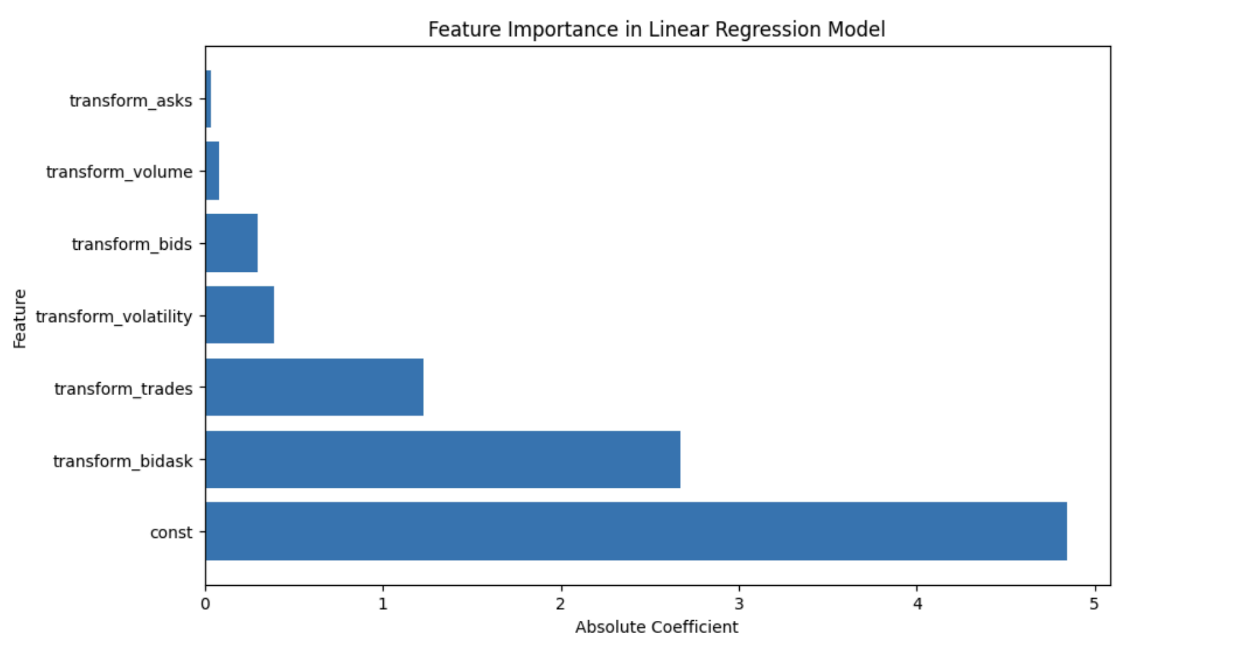

Figure 12:
Feature Importance in Linear Regression

III. Results

This section presents the findings of the comparative analysis of liquidity metrics and their impact on Bitcoin price dynamics. The analysis involves correlation studies and the application of machine learning models, specifically Random Forest, XGBoost, and Linear Regression, to evaluate the predictive power of various liquidity indicators. The log-transformed price of Bitcoin on Figure 1 over the past five years shows the significant fluctuations and overall upward trend in its value. This provides a baseline for understanding how various liquidity metrics correlate with Bitcoin's price movements. The next few figures provide visual insights into how liquidity indicators have evolved and potentially influenced Bitcoin prices. Figure 2 with the Log Volatility shows the fluctuations in Bitcoin's volatility, indicating periods of high and low market stability. Figure 3 with the Log number of transactions illustrates the frequency of Bitcoin transactions over time, reflecting market activity. Figure 4 with the Log Asks price captures the minimum amount someone is willing to accept for something in the market. Figure 5: Log Bids captures the maximum someone is ready to offer for something in the market. Figure 6 with the Log Bid-Ask Spread shows the difference between the highest bid and the lowest ask prices, indicating market liquidity. A correlation analysis was conducted to examine the relationships between Bitcoin prices and the selected liquidity metrics. The results indicate significant correlations between Bitcoin prices and various liquidity factors, highlighting their potential impact on price movements. The highest correlation was found between volatility and Bitcoin prices, as volatility is identified as the most significant predictor of Bitcoin prices in both the Random Forest and XGBoost models, with more than 60% importance. In contrast, the number of trades exhibited the lowest correlation, contributing less than 5% to the models' predictive power.

I used three machine learning models to predict Bitcoin prices based on liquidity metrics: Random Forest Regressor, XGBoost, and Linear Regression. The performance of each model was evaluated using R-squared values.

Model	R squared score
XGBRegressor	0.91
Linear Regression	0.78
Random Forest Regressor	0.91

Table 1:
This table shows the R-squared score for the XGBRegressor, Linear Regression, and Random Forest Regressor Models.

The Random Forest Regressor and XGBoost Regressor demonstrated the highest predictive accuracy with an R-squared value of 0.91, followed by Linear Regression. Figure 7 shows the scatter plot of predicted vs. true values for the Random Forest model. It shows a strong alignment, indicating high predictive accuracy. The scatter plot for the XGBoost in the Figure 8 model also shows strong alignment, with the same R-squared value of 0.91. The scatter plot in Figure 9 for the Linear Regression model shows a lower alignment compared to the other models, with an R-squared value of 0.78. The feature importance plot for the Random Forest model in Figure 10 indicates that volatility is the most significant predictor of Bitcoin prices, followed by other liquidity metrics. The XGBoost model in Figure 11 also highlights volatility as a key feature, consistent with the Random Forest model. The Linear Regression model in Figure 12 identifies bid-ask spread as the most influential factor, differing from the other models.

The results underscore the critical role of liquidity metrics in predicting Bitcoin prices. Volatility emerged as the most informative feature in both the Random Forest and XGBoost models, highlighting its significant influence on Bitcoin price dynamics. The high predictive accuracy of the Random Forest model, with an R-squared value of 0.91, suggests that incorporating liquidity indicators can substantially enhance the understanding and forecasting of Bitcoin price movements.

Despite efforts to conduct a thorough analysis, several limitations must be acknowledged in this research, which may impact the interpretation and generalization of the findings:

Data Quality and Availability: The analysis heavily relies on data availability and quality from the external source data.bitcoinity.org. While efforts were made to ensure the reliability of the data, inaccuracies or inconsistencies within the dataset could introduce biases or limitations to the analysis.

Selection of Liquidity Indicators: The choice of liquidity indicators is subjective and may not capture the full spectrum of liquidity dynamics within the Bitcoin market. Alternative indicators or additional dimensions of liquidity not included in this study could yield different insights into the relationship between liquidity and Bitcoin prices.

Correlation vs. Causation: The analysis primarily identifies correlations between liquidity factors and Bitcoin prices. However, establishing causality between liquidity dynamics and price movements is challenging due to market dynamics' complex and multifaceted nature. Other unobserved variables or external factors may influence liquidity and Bitcoin prices, confounding the interpretation of results.

Market Conditions and Dynamics: The analysis spans a specific period, and market conditions and dynamics during this period may not be representative of all market environments. Changes in regulatory policies, technological advancements, macroeconomic factors, or market sentiment could influence liquidity dynamics and Bitcoin prices differently over time.

Sample Size and Timeframe: The analysis encompasses a five-year timeframe, which may limit the generalizability of findings to other time periods. Additionally, the dataset's sample size may not capture all relevant variations and patterns in liquidity and Bitcoin prices, particularly during extreme market volatility or structural shifts.

Model Complexity and Simplifications: The analysis may employ simplified models or methodologies to explore the relationship between liquidity and Bitcoin prices. While these simplifications facilitate interpretation and analysis, they may oversimplify the underlying mechanisms governing liquidity dynamics and price movements, leading to potential biases or inaccuracies.

Conclusion

In conclusion, this study offers a foundational understanding of the intricate relationship between liquidity and Bitcoin price dynamics. While the analysis reveals the correlation between liquidity indicators and Bitcoin prices, it also opens avenues for future research to delve deeper into this complex relationship. Future studies could explore additional liquidity metrics beyond those considered in this analysis, such as depth of order book, market depth, and transaction cost metrics, to gain a more comprehensive understanding of liquidity dynamics in cryptocurrency markets. Moreover, employing advanced analytical techniques, including machine learning algorithms and time-series modeling, could provide further insights into the nuanced interactions between liquidity and price movements. Additionally, considering broader market and behavioral factors, such as investor sentiment, regulatory developments, and macroeconomic indicators, would enrich our understanding of the drivers of liquidity and price in cryptocurrency markets. By addressing these research gaps, future studies can contribute to developing more robust trading strategies, enhance market efficiency, and provide valuable insights for regulatory decision-making in the rapidly evolving cryptocurrency landscape.

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