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Research Article

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Financial Market Characteristics: A Quantitative Study of Volatility, Liquidity and Correlation

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Abstract

The study used advanced statistical techniques and programming python based statistical analysis to assess vital market characteristics such as correlations, volatility and liquidity. The major gap in the existing literature comes from the lack of unified framework that integrates volatility, liquidity and correlation on the market segment, which results into fragmented insights that helps analyst, investors, policy makers making the right decisions. This study managed to fill this gap by deploying an inclusive analytical framework to explore patterns on three market segment S&P 500, NASDAQ Composite and Dow Jones Industrial Average for duration of 9 years from 2015 to 2024. The study findings revealed different practical insight for risk management, optimizing portfolios and policy making using machine learning predictions.

Keywords: Liquidity, Volatility, Correlation

1. Introduction

The financial markets behavior shaped by different interrelated dimensions such as liquidity, volatility and correlations and each plays its role in investment strategy and risk management. The three dimensions was often analyzed independently which limit different data users to gain a comprehensive insight from how they can interact each other during boom periods. The main goal of this study was to develop a unified framework that captured the interaction between correlation, volatility and liquidity, enhancing decision making capabilities from different data users. The usage of market data from major U.S indices (DJIA, NASDAQ and S&P 500) helped to explores how these three dimensions evolved over time, impact portfolio management and policy formulation by applying machine learning techniques to enhance predictions for market behavior.

2. Problem Statement

The financial markets exhibit different complex statical characteristics that are essential for risk management, investment strategies and policies formulation. Even though asset correlations, liquidity and volatility play a significant role in determinants of market dynamics, current research mostly analyze these dimensions independently, leading to fragmented insights and affect decision-making. The existing gap presents a substantial challenge, despite the availability of financial data, there exists a market disconnection between availability of data and application and integration of different statical method that can provide a comprehensive market insight. The existing use of volatility, liquidity and correlations independently limits our capacity to identify different interconnected insights that impacts the market behavior. This scenario becomes worse for modern market dynamics as traditional frameworks failed to oversee the evolving nature of market relationships, especially in technology-driven sectors and in periods of market stress. Different market segments faced practical application challenges in conducting market analysis in investment and risk management strategies. This predominantly observed in portfolio optimization decisions needing volatility, correlation dynamics, risk analysis frameworks that need to account for liquidity conditions during market stress period and development of trading strategy that can balance the execution costs with market impact. The study addressed the identified challenges by developing a unique analytical framework that examines the interdependency between volatility, corrections and liquidity. Employing of different advanced statistical methods and machine learning techniques, the study aimed to identify different patterns of these market characteristics, quantifying their impact on market efficiency and stability, develop practical insights for management of risks and optimizing portfolio and provide actionable recommendations for policy makers and different market players.

3. Literature Review

The development of financial market analysis has seen a noteworthy progress in understanding individual market features, yet gaps persisted in examining the interconnectedness among those statistical approaches. Mandelbrot in (1963), in his study revealed that financial returns deviate from normal distribution which challenged the traditional assumptions of market behavior. Engle's in (1982) and Bollerslev's (1986) played a major part in the industry by developing the ARCH and GARCH modes which furthered improved the volatility analysis Modern research study had significantly developed further based on these fundamentals. In their study Huang et al. (2019) has revealed that the analysis of volatility of volatility was affected the index returns which goes beyond the traditional volatility analysis. This was enhanced further by the study of Zhang, Choudhry, and Kuo (2021) where they investigated the relationship between liquidity, equity returns and investors risk aversion which then played in the predictability of the variance risk premium (VRP). The understanding of market liquidity has been substantially enhanced by recent research. In their study Pereira and Zhang (2010) revealed major insights which showed that stock returns decreased with increased volatility due to liquidity factors. Their study emphasized on multiple liquidity metrics need beyond the traditional volume measures amongst market depth indicators and bid-ask spreads. The multidimensional methods inclusion on liquidity analysis has now dominated the modern market analysis.

In terms of correlation analysis studies, Markowitz's (1952) and Sharpe's (1964) provided the theoretical foundation in portfolio theory and CAPM however, modern research revealed that the correlation during market stress periods varied significantly and not static. This correlation effects have affected the portfolio diversification and risk management strategies. The integration of these market characteristics remains an emerging focus in current research. Modern analytical capabilities, powered by machine learning and big data analytics, enable more sophisticated analysis of market interrelationships. However, significant gaps remained in understanding better the dynamic interactions, especially the effect of volatility regimes on market liquidity and correlation structures and also the impact different liquidity conditions on assets volatility in terms of diversification benefits and identification of role of different specific sector factors that drives market.

4. Theoretical Framework

4.1 Volatility Analysis

Volatility of an indices/asset measures the extent to which its price fluctuates over time. The study applied standard deviation and GARCH model to estimate volatility. The annualized volatility formular was:

$$\sigma = \sqrt{252}\ x \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2} \qquad (1)$$

where:

- r_i: daily return on day i
- $\bar{r}$: Average daily return
- N = trading days number
- 252 = trading days per year (working days)

The GARCH (1,1) model used to predict the future volatility was given by the following formular:

$$\sigma 2t = \alpha_0 + \alpha 1\epsilon^2_{t-1} + \beta 1\sigma 2_{t-1} \qquad (2)$$

Where:

- σ^2_t The conditional variance
- $\epsilon^2 t_{-1}$ Error term (past)
- $\alpha_0, \alpha_1, \beta_1$ Parameters

4.2 Liquidity Analysis

The liquidity reflects how an asset can easily be traded without impacting its price. The study measured liquidity used trading volume and bid-ask spread.

Average daily trading volume

$$Liquidity\ (volume) = \frac{1}{n}\sum_{i=1}^{n} V_i \qquad (3)$$

Where:

- V_i: Trading volume on day i.

Bid-Ask Spread:

$$Bid\ Ask\ Spread = \frac{Ask\ Price - Bid\ Price}{Mid\ Price} \qquad (4)$$

The above metric captured transaction costs and market depth.

4.3 Correlation Analysis

The formular for measuring correlation between assets X and Y was:

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \qquad (5)$$

Where:

- Cov(X,Y): Covariance between X and Y
- σ_x *and* σ_y: Standard deviations of X and Y
- The high correlations imply limited diversification benefits which was explored over time using rolling correlations matrices.

5. Methodology

5.1. Data Collection Techniques

The study collected daily historical data from yahoo finance website using python on three variables index stock prices, bid-ask spreads and trading volume for major U.S indices (DJIA, NASDAQ and S&P 500) for period from 01 January 2015 to 22 October 2024.

5.2. Data Processing

After data collection, the datasets was cleaned using python by ensuring consistency across there indices (DJIA, NASDAQ and S&P 500) and dealing with missing values and calculated indices returns using the following formula:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (6)$$

5.3 Statistical and Machine Learning Tools

The study used four different statistical and learning tools:

- Liquidity
- LSTM networks
- Volatility
- Correlation

6. Findings

6.1. Volatility Analysis

The volatility analysis reveals a significant spike for 3 indices during periods of market stress, especially in early 2020 due to Covid 19 pandemic. The study observed that the NASDAQ index persistently showed higher market volatility compared to other indices (S%P 500 and DJIA) mainly due to the reasons of its higher concentration of technology stocks which tend to be more fluctuating.

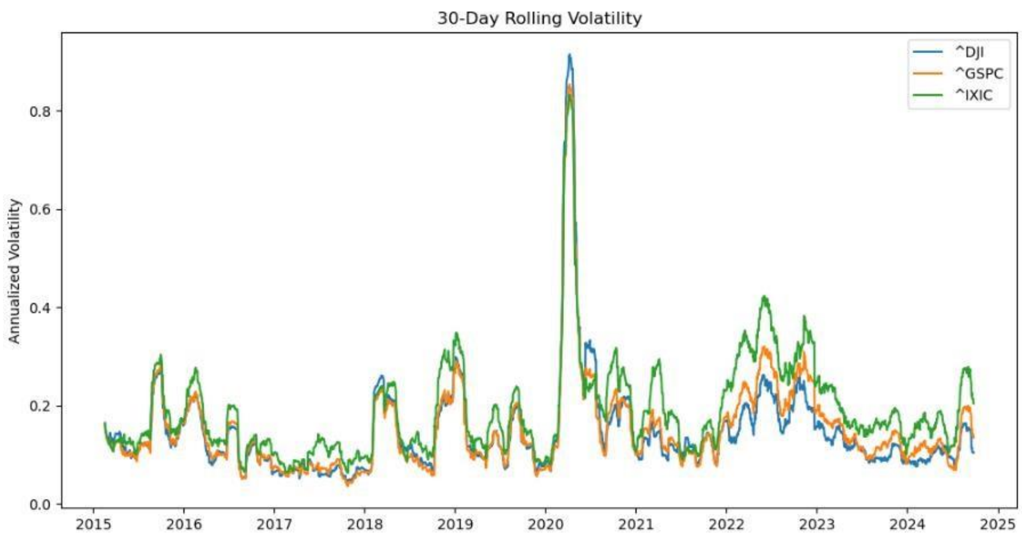

Figure 1: Annualized volatility

6.2. Liquidity Analysis

The study did the liquidity analysis using a 30-day rolling average trading volumes for three indices for the whole study period and it revealed that NASDAQ had the highest trading volumes compared to other two indices hence reflected its increased market activity for the study duration due to its concentration of technology of stocks on the market. The S&P 500 index maintains a steady volume around one million, with slight fluctuations throughout the study period while the DJIA exhibited the lowest volume, indicating its smaller set of component stocks. The study reveals that NASDAQ's volume peaks more frequently, mostly during volatile periods, implying that the investors were more active in tech-heavy markets, potentially strengthening market liquidity and volatility.

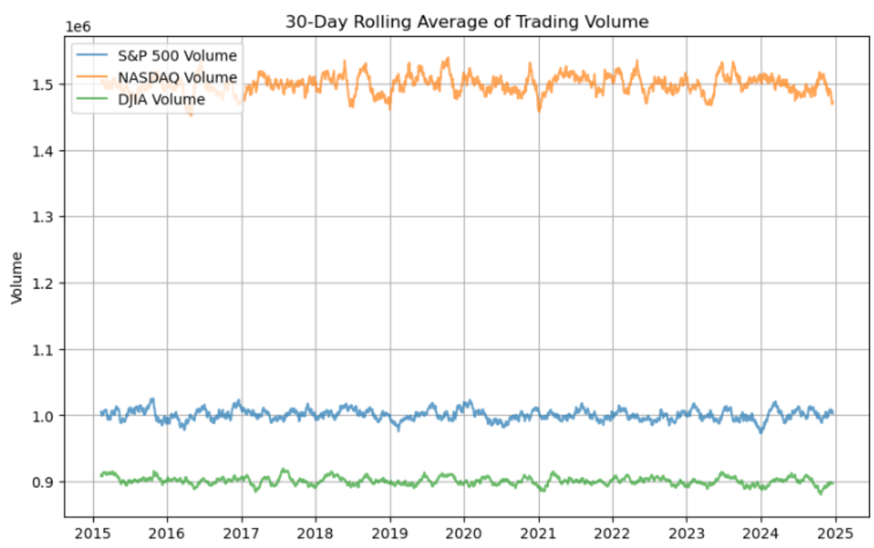

Figure 2: 30-Day Rolling Average of Trading Volume

6.3. Correlation Analysis

The correlation analysis reveals that the correlation between NASDAQ and DJIA was high and stable near 1 for the study period which indicated a strong positive linear relationship between the two indices throughout the study period. The correlation between S&P 500 and NASDAQ reveals more fluctuation, oscillating between positive and negative correlation which shows that the relationship between these indices was unstable, mainly influenced by market conditions and sector specific events. The negative correlation periods imply the diversification opportunities exists among two indices (S&P 500 and NASDAQ) while high positive fluctuations reflet the dynamic nature of the financial markets during the observed study durations.

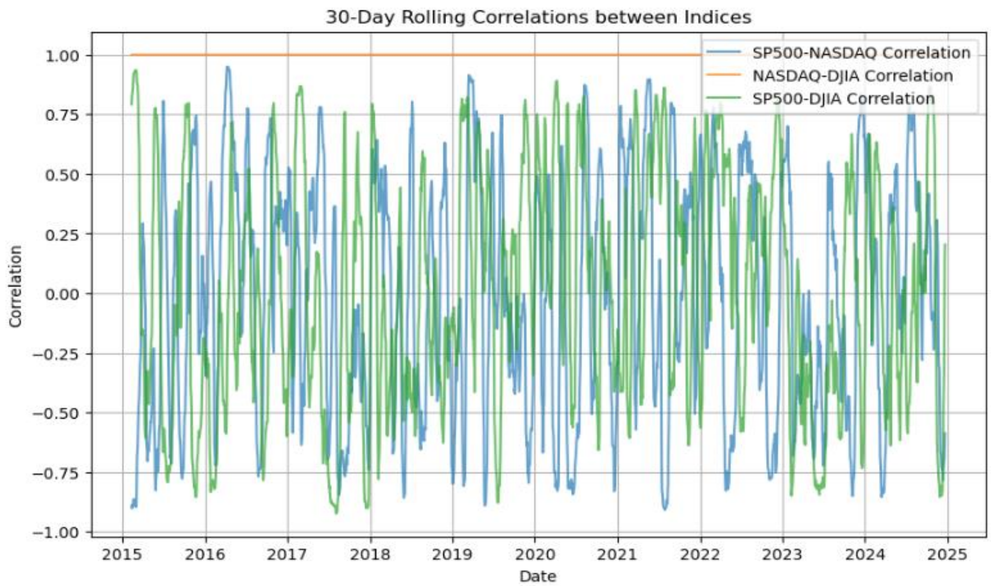

Figure 3: 30-day Rolling Correlations

7. Discussions

The volatility analysis reveals that all tree indices experienced significant spikes in early 2020 due to onset of the Covid-19 pandemic. Among the three indices in our portfolio, NASDAQ consistently showed higher volatility compared to other indices throughout the study duration. This higher volatility of NASDAQ index attributed to its focus on the technology stocks, which experience larger price fluctuations due to innovations, market sentiment, pandemics and higher expectation growth [1]. The findings aligned with the say that the heavily technology indices are more disposed to market disruptions, as seen during both pandemic-driven volatility and following recovery phases. The liquidity analysis reveals that the NASDAQ index had the highest trading volumes over the study duration which reflects the relevance increase in market activity especially in technology sector where investors were active in speculative and growth driven markets. The S&P 500 contrary maintained a steady volume of around one million with a slight fluctuation which shows stable market participation across its diverse range of sectors. The DJIA observed the lowest volume record among all three indices which aligns with the smaller number of components stocks within the index and its focus on more established, blue-chip companies.

The frequent volumes peaks observed for the NASDAQ index often concurring with periods of sensitive market volatility support the idea that investors become more active during uncertain times which implies both liquidity and volatility (Engle, 1982). The strong market involvement of NASDAQ during volatile period shows that liquidity while beneficial for trade execution, can also increase the spread of shocks during downturns. The correlation analysis reveals a strong positive relationship between NASDAQ and DJIA indices, constantly near 1 throughout the study duration. Both indices moved in tandem, indicating limited diversification benefits between them. The correlation between S&P 500 and NASDAQ were between positive and negative correlation which implies that their relationship was unstable and these fluctuations mostly caused by the market drivers like changes in technology stocks or macroeconomic factors [2]. The presence of negative correlation between S&P 500 and NASDAQ during volatile periods reflects potential diversification benefits for investors. Diversification benefits occur when indices move in different direction which reduce the overall portfolio risks [3].

8. Conclusions

The study provided insights into different market characteristics such as volatility, correlations and liquidity across three major U.S indices (S&P 500, NASDAQ and DJIA) for the duration between 2015 and 2024. The volatility analysis highpoints the determined fluctuations in the NASDAQ index motivated by the technology sector's inherent sensitivity to market shocks. The liquidity analysis approved that NASDAQ's higher trading volume aligns with its role as the leading platform for tech stocks shows that the liquidity tends to increase during volatile periods enhancing both opportunities and risks for market participants. The study reveals strong positive relationship between NASDAQ and DJIA while NASDAQ and S&P 500 had negative and positive relationship which shows unstable market conditions. The negative correlation between indices present diversification opportunities where investors can minimize the potential risks by allocating resources across those indices. In summary, the findings highlight the role of monitoring volatility, liquidity and correlations of an index or market segment in portfolio management and risk assessment. Different market players such as investors and policymakers can benefit from these insights by updating or incorporating different strategies according to the market dynamics change of the financial markets mostly in the technology driven sectors [4-12].

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