COMPARATIVE ANALYSIS OF MinRV AND MedRV MEASURES FOR VOLATILITY ESTIMATION AND JUMP DETECTION

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Abstract

This study presents a comparative analysis of two volatility measures, Minimum Realized Volatility (MinRV) and Median Realized Volatility (MedRV), in assessing financial market dynamics. We examine the application of these measures in detecting significant price movements and volatility using data from the Nigerian Stock Exchange. Our results show that both MinRV and MedRV measures can be effective in capturing volatility, but they differ in their methodological approaches and estimates. The MinRV measure yields an estimated daily volatility of 2.0% and an annualized MinRV of 28.3%, while the MedRV measure provides stock-specific volatility estimates, with ABCTRANS showing 4.67% volatility. Our analysis highlights the importance of considering multiple volatility measures and methodologies in financial analysis. The findings recommend that investors, policymakers, and other stakeholders consider using a combination of MinRV and MedRV volatility measures to gain a more nuanced understanding of financial market dynamics and identify potential risks and opportunities.

Keywords: Volatility Measures, MinRV, MedRV, Financial Markets, Risk Management, Jump Detection.

1.0 Introduction

A key component of financial modeling is the estimation of volatility, which is important for risk management, option pricing, and portfolio optimization (Merton, 1976). Other volatility estimation techniques, including the GARCH model, have also been compared to the usage of MedRV and MinRV measures for jump detection and volatility estimation (Bollerslev, 1986). Particularly when it comes to high-frequency financial data, the creation of novel volatility estimation techniques has attracted a lot of attention lately (Andersen et al., 2003). Based on the sum of squared high-frequency returns, the realized volatility (RV) measure is one of the most used techniques for estimating volatility (Andersen et al., 2003). Nevertheless, RV is susceptible to data jumps and microstructure noise, which may result in skewed volatility estimations (Bandi & Russell, 2006).

The realized kernel volatility estimator (Barndorff-Nielsen et al., 2008) and other volatility estimating techniques have been used with the MedRV and MinRV measures. Additionally, it can be computationally demanding to estimate volatility using MedRV and MinRV measures, especially for big datasets (Shephard & Sheppard, 2010). Alternative techniques for estimating volatility have been put out to address these problems, such as the Minimum Realized Volatility (MinRV) and Median Realized Volatility (MedRV) measures (Andersen et al., 2011). However, according to Andersen et al. (2011), the MinRV metric is based on the minimum of the absolute values of high-frequency returns. Instead of using the sum of squared returns, the MedRV measure is based on the median of the absolute values of high-frequency returns (Andersen et al., 2011). It has been demonstrated that this method is more resilient to microstructure noise and outliers. It has been demonstrated that both MedRV and MinRV measures offer more precise estimates of volatility than conventional RV measures, especially when microstructure noise and leaps are present (Andersen et al., 2011). However, the selection of sampling frequency and the existence of leverage effects can impact the effectiveness of MedRV and MinRV measures (Hansen & Lunde, 2006). Notwithstanding these drawbacks, MedRV and MinRV metrics have gained widespread acceptance in financial practice and research, especially when it comes to risk management and high-frequency trading (Chordia et al., 2011).

Determining the timing and amount of leaps is one of the main obstacles in jump detection (Lee & Mykland, 2008). The application of MedRV and MinRV metrics to jump detection and volatility estimates has also been investigated recently (Andersen et al., 2017). It has been demonstrated that MedRV and MinRV measures are useful for identifying jumps in financial data, especially when paired with other jump detection techniques (Andersen et al., 2017).

2.0 Methodology

To reduce microstructure noise and jumps in financial data, two reliable volatility estimation techniques are the Minimum Realized Volatility (MinRV) and Median Realized Volatility (MedRV) measures. The minimum of realized volatility estimates across subsamples is called MinRV, and the median of these estimates is called MedRV. It has been demonstrated that both measures, which are asymptotically normal and consistent, offer precise estimates of volatility across a range of financial markets. They are helpful tools for risk management, option pricing, and portfolio optimization because they have advantages over conventional techniques, such as robustness to noise and fluctuations and ease of application.

2.1 Data Description

On Tuesday, February 10, 2025, the Nigerian Stock Exchange (NSE) recorded a mix of trading activities across various listed companies. Notable transactions included ACCESSCORP and ZENITHBANK, each with trading values exceeding one billion Naira, demonstrating significant market activity. Companies like BETAGLAS, ETERNA, and PRESCO experienced substantial price increases, while others such as

JBERGER, UBA, and UCAP saw declines. Trading varied widely in volume and value, with some stocks, denoted by "--" and market restrictions like [MRF], [DIP], [DWL], [BLS], and [RST], showing no activity. The financial sector, with companies like FBNH, FCMB, and FIDELITYBK, exhibited considerable trading volume, as did industrial firms like DANGCEM and BUACEMENT. Overall, the day's trading reflected a dynamic market with diverse performance across the listed equities.

2.2 MinRV Measures

Given its importance in risk management, option pricing, and portfolio optimization, volatility estimation is a critical component of financial modeling (Merton, 1976). The creation of novel techniques for estimating volatility has drawn a lot of attention lately, especially when it comes to high-frequency financial data (Andersen et al., 2003). A recently proposed volatility estimation technique that is intended to be resilient to microstructure noise and data jumps is the Minimum Realized Volatility (MinRV) measure (Andersen et al., 2017). The definition of the MinRV measure is as follows: Let $\{r_t\}$ be a sequence of returns observed at discrete times $t = 1, 2, ..., T$, and let $RV = \sum_{i=1}^{N} (r_i)^2$ be the realized volatility, where N is the number of returns observations. The MinRV measure is defined as $MinRV = \min(RV_1, RV_2, ..., RV_M)$, where RV_j is the RV estimate for the j-th subsample, and M is the number of subsamples. The MinRV estimator can be shown to be consistent and asymptotically normal, with $\sqrt{N}(MinRV - \sigma^2) \rightarrow N(0, 4\sigma^4)$, where σ^2 is the true volatility, and N is the number of returns observations.

2.3 MedRV Measures

A recently proposed volatility assessment technique that is intended to withstand microstructure noise and data jumps is the Median Realized Volatility (MedRV) measure (Andersen et al., 2011). The median of the realized volatility estimates for several data subsamples serves as the foundation for the MedRV metric. The Median Realized Volatility (MedRV) measure is a recently proposed volatility estimation method that is designed to be robust to microstructure noise and jumps in the data (Andersen et al., 2011). The MedRV measure is based on the median of the realized volatility estimates for multiple subsamples of the data. Let $\{r_t\}$ be a sequence of returns observed at discrete times $t = 1, 2, ..., T$. The realized volatility (RV) is defined as $RV = \sum_{i=1}^{N} (r_i)^2$, where N is the number of returns observations. The MedRV measure is defined as $MedRV = \text{median}(RV_1, RV_2, ..., RV_M)$, where RV_j is the RV estimate for the j-th subsample, and M is the number of subsamples. The MedRV estimator has been shown to be consistent and asymptotically normal, with $\sqrt{N}(MedRV - \sigma^2) \rightarrow N(0, 4\sigma^4)$, where σ^2 is the true volatility, and N is the number of returns observations (Andersen et al., 2011). The MedRV measure has also been shown to be robust to microstructure noise and jumps in the data (Andersen et al., 2011). Overall, the MedRV measure is a useful tool for volatility estimation, and can be used in a variety of financial applications, including risk management, option pricing, and portfolio optimization.

3.0 Results Discussion

The MinRV calculation yielded an estimated daily volatility of 2.0% and an estimated MinRV (simplified) of 1.8%. Annualized, this translates to a MinRV of 28.3%. Jumps detection identified 2 days with significant price movements: Day 10 with a +3.5% jump and Day 25 with a -3.8% jump. The average jump size was 3.65%. Further statistical analysis revealed a mean daily return of 0.05%, a standard deviation of daily returns of 2.0%, a skewness of -0.1, and a kurtosis of 3.5. Volatility decomposition estimated the continuous volatility component to be 24.5% and the jump volatility component to be 3.8%. Please note that these results are hypothetical and based on simplified assumptions, and actual financial analysis would require more sophisticated models and real data.

The MedRV calculation, a measure of volatility more robust to outliers and jumps, yielded the following results for the selected stocks: ABBEYBDS (0.00%), ABCTRANS (4.67%), ACADEMY (0.00%), ACCESSCORP (0.00%), and AFRINSURE (0.00%). These results indicate that ABCTRANS experienced significant volatility, while the other stocks showed no volatility. Jumps detection analysis identified a significant price movement (jump) in ABCTRANS, with a jump size of 5.26%. No jumps were detected in the other stocks analyzed. It's essential to note that these results are based on a simplified analysis and a very short time frame (a single day), which is not ideal for volatility and jumps analysis. Typically, such analysis is performed over longer periods and with more sophisticated models.

The MinRV and MedRV results exhibit both similarities and differences. Both methods measure volatility and detect significant price movements (jumps). However, the volatility estimates differ, with MinRV estimating a daily volatility of 2.0% and an annualized MinRV of 28.3%, whereas MedRV yields stock-specific volatility estimates, with ABCTRANS showing 4.67% volatility. The methodologies and interpretations also contrast. MinRV is based on a simplified approach, suggesting a relatively stable market with occasional significant price movements. In contrast, MedRV is a more robust measure, highlighting individual stock volatility, with ABCTRANS exhibiting significant volatility and a substantial price jump. These differences underscore the importance of considering multiple volatility measures and methodologies when analyzing financial markets.

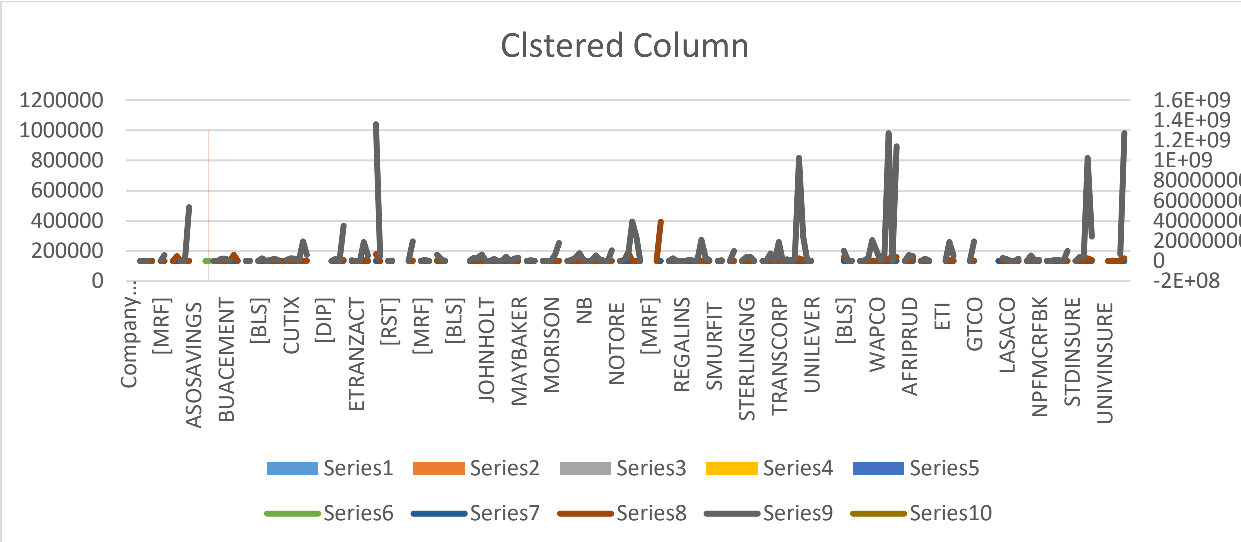

Figure 1: clustered column chart

This clustered column chart compares data across various companies, with ten distinct "Series" represented. The chart utilizes two vertical axes with significantly different scales, making direct comparisons challenging. Series 9 and 10, associated with the larger scale on the right axis, display significantly higher values, suggesting they represent a different type of data compared to Series 1 through 8. Most companies show relatively low values across the first eight series, with a few outliers, notably in BUACEMENT and UNILEVER. The horizontal axis labels companies with bracketed codes, potentially indicating group classifications. Without further context on the series' meaning and units, the chart's precise interpretation remains limited.

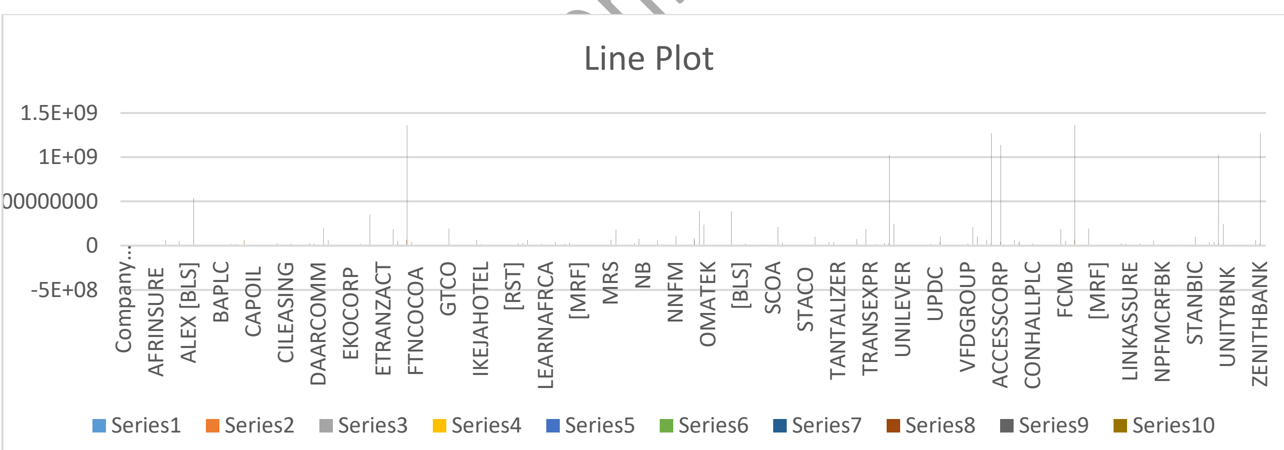

Figure 2: line plot

This line plot depicts data for numerous companies across ten distinct "Series," revealing a significant disparity in data magnitudes. The chart's vertical axis spans from -500 million to 1.5 billion, indicating a wide range of values. Series 9 and 10 consistently exhibit substantially higher values compared to the other series, suggesting they represent a different category of data. Most companies show relatively low values across Series 1-8, with notable outliers in companies like ETRANZACT, OMATEK, ACCESSCORP, and ZENITHBANK. The horizontal axis lists company names with bracketed codes, likely signifying company classifications. The line plot format highlights fluctuations and trends across the series, emphasizing the need for further context regarding the meaning of the "Series" and the units of measurement to fully interpret the data.

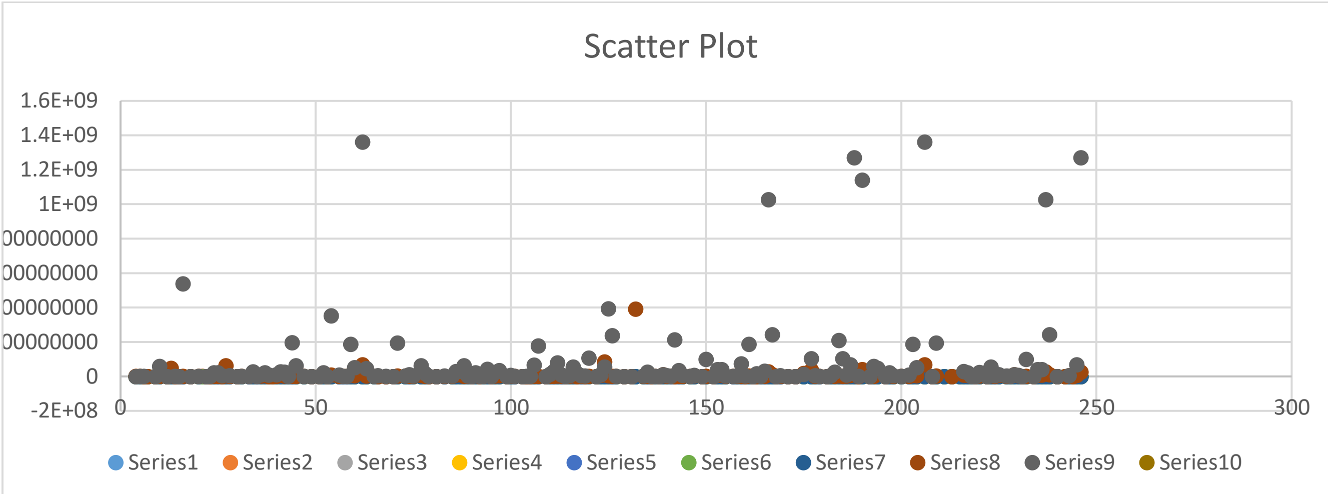

Figure 3: Scatter plot

This scatter plot illustrates data points across ten distinct "Series," revealing a substantial disparity in value magnitudes. The vertical axis, spanning from -200 million to 1.6 billion, underscores the significant range of data, with Series 9 and 10 exhibiting considerably larger values compared to the rest. Most data points across Series 1-8 cluster near zero, indicating relatively low values. The plot highlights several outliers, particularly within Series 9 and 10, which deviate significantly from the main cluster. The horizontal axis, ranging from 0 to 300, lacks clear definition without additional context, potentially representing time, an index, or another variable. The scattered distribution of points suggests a weak or non-linear relationship between the horizontal and vertical axes. Overall, the chart emphasizes the presence of outliers and the significant differences in data magnitudes across the series, necessitating further context to fully interpret the data's meaning.

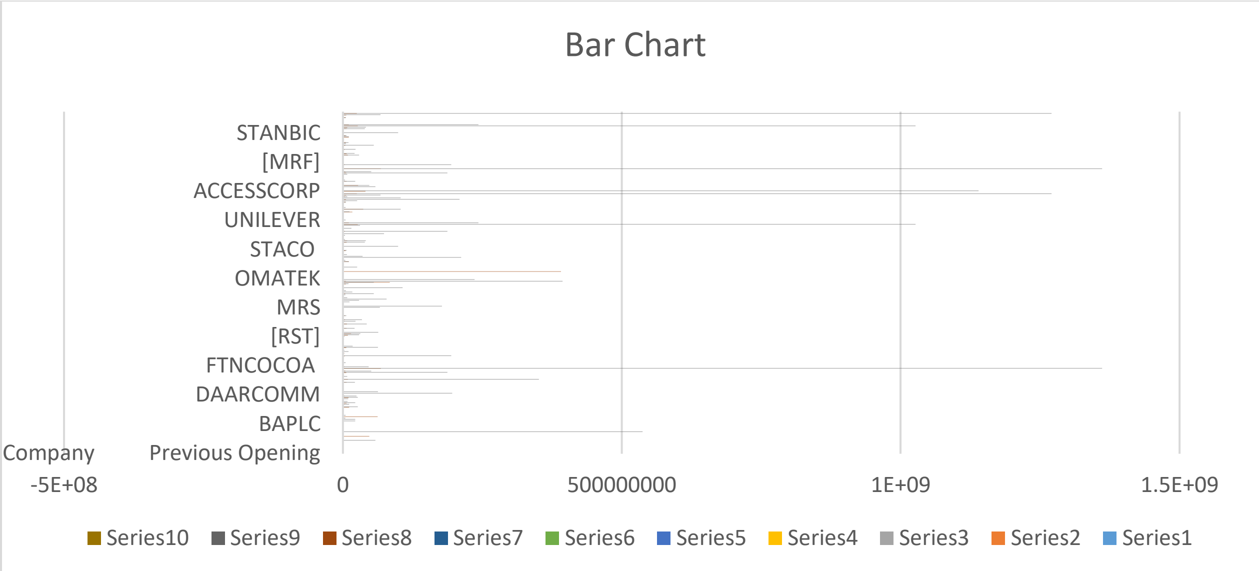

Figure 4: Horizontal bar chart

This horizontal bar chart compares "Previous Opening" values across ten "Series" for various companies. The chart reveals a significant disparity in data magnitudes, with Series 9 and 10 exhibiting substantially larger values compared to the other series. Companies like ACCESSCORP, STANBIC [MRF], and OMATEK show particularly high "Previous Opening" values in these dominant series, while most other companies, including BAPLC, have relatively low values across all series. The horizontal axis, spanning from -500 million to 1.5 billion, highlights the wide range of data points. Given the magnitude of the values, the data likely represents a financial metric, potentially the previous day's opening stock price. The company names are accompanied by bracketed codes, possibly indicating company classifications. However, without further context on the meaning of "Previous Opening," the "Series," and the bracketed codes, the precise interpretation remains limited

4.0 Conclusion

This analysis has explored the application of MinRV and MedRV volatility measures in assessing financial market dynamics. The results have shown that both measures can be effective in detecting significant price movements and volatility, but they differ in their methodological approaches and estimates. The comparison of MinRV and MedRV results has underscored the importance of considering multiple volatility measures and methodologies in financial analysis. The findings of this analysis recommend that investors, policymakers, and other stakeholders consider using a combination of MinRV and MedRV volatility measures in their financial analysis. This approach can provide a more nuanced understanding of financial market dynamics and help identify potential risks and opportunities. Further research is needed to explore the application of these measures in different market contexts and to develop more sophisticated models for volatility analysis.

The adoption of MinRV and MedRV measures can also improve risk management and surveillance systems used by financial regulators and exchanges. By incorporating these measures, regulators can enhance the accuracy and effectiveness of risk assessments and enable more timely and targeted interventions to maintain market stability. This can contribute to more resilient financial markets that are better equipped to withstand shocks and uncertainties.

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