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# Enhancing Predictive Accuracy in Equity Markets: An Empirical Analysis of Outlier Robustness and Forecasting Efficiency in Dow Jones Index Returns

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**Abstract**
*This paper empirically examines methods for the detection of outliers and their effect on forecast accuracy in financial time series data using a number of criteria that have been found to discriminate among forecast methods. We have used daily returns from the Dow Jones Index (April 2002–June 2024) where we divide the sample into an in-sample estimation period (April 2002–May 2023) and an out-of-sample (1-year) forecasting window (June 2023–June 2024). In this paper, we also compare the above six outlier detection methods with three volatility forecasting models (GARCH and its extensions) to measure the impact of those synergistic effects on prediction.*
*We show that outlier removal systematically improves the precision of models, reflected in reductions in average mean absolute error (MAE) and mean absolute percentage error (MAPE). The MADe Method is found to be the best outlier detection method, and the three models produce better predictions in all cases (GARCH: ΔMAPE = −18.3%, ΔMAE = −12.7%; EGARCH: ΔMAPE = −14.9%; GJR: ΔMAPE = −11.2%) also in both fields two auxiliary methods, namely Tukey's Method and VH Boxplot, are respectively the second and third best outlier detection method. We observe that, in both outlier-adjusted and unadjusted cases, their GARCH versions consistently exhibit better performance compared to the respective asymmetric models (i.e., EGARCH and GJR), suggesting a better ability of GARCH under standard setting to address leptokurtic shocks but when associated with MADe-based filtration.*
*The best process, which includes MADe outlier method within GARCH(1, 1) forecasting, decreases overall autocorrelation forecast errors by 22.4% below benchmark levels. The obtained findings have important implications for quantitative finance for the purpose of developing better approaches to modeling volatility and for improving risk management in equity markets.*
**Keywords:** *Equity Markets*, *Outliers Detection, MADe Method, Forecasting, GARCH Models.*

## 1. Introduction

The detection of Outliers is very Importance in Financial time series analytics, particularly on Financial planning and Risk Management. Outliers can sometimes be introduced due to major

macroeconomic events, market irregularities, or errors in recorded data. Outliers are single observations that are substantially different from the other observations in the dataset, and have the ability to influence financial models, forecasting accuracies, decision making and research results to a great extent. There are, however, outliers in nearly all financial time series data and they can have a significant impact on statistical measures, cause biased estimates, and result in incorrect conclusions. In particular, in the presence of outliers one may observe biased distributions, exaggerated volatility, ill-fitted models for algorithmic trading, risk measure and portfolio optimization, etc. Therefore these outliers should be measured or managed appropriately or else it can turn in to bad/formative investment strategies, along with incomplete risk analysis and may even loose (Cont 2001, Rousseeuw & Leroy 2005).
One of the special cases when outlier detection can become very useful is when working with major financial indices, such as the Dow Jones Industrial Average (DJIA). These indices serve as a valuable barometer in international financial markets where sectors are compared across markets. These indexes can change dramatically due to sudden market shocks, changes in monetary or fiscal policy, or some sort of surprising financial news. The effects can be enormous, including investment choices and regulatory reactions and market psychology. The correct classification of an outlier from most return series and the proper handling of the outlier one can prevent misleading performance results due to the outlier, which can have profound consequences on financial forecast and sound risk management strategies (Bollerslev, 1986; Verbeek, 2017).
Outlier detection in financial time series is crucial. Maronna et al. (2019) reported that a strong application of outlier detection methods is one of the critical factors in maintaining the integrity of the financial data and it will remain a robust mirror of the typical market conditions and it increases the integrity very much. obscured in traditional market patterns. More importantly, the identification of real outliers in the market as opposed to (transitory or non-systemic) anomalies is important for scientific parsing of financial data, as well as for evidence-based investing (Tsay, 1988).
Outliers of financial time series data are an important term for risk management and financial planning process, and the purpose of this report is to understand the risks. It also investigates several techniques for detecting outliers, examines their usefulness in several financial fields, and addresses the contribution of outlier management into hot topics of financial decision. The explanation confines itself to an examination of outliers in the DJIA indices, because they are some of the most important market indicators.
This study is carried out to compare six conventional outlier detection methods and three forecasting GARCH type models for financial time series data.

## 2. Review of Literature

Detection of outliers from financial time series data and its implication on accuracy of forecasting has been one of the focal areas of research of the last few years, with numerous papers examining various methods for enhancing predictive power. The recent literature (2020–2025) indicates growing significance of effective outlier detection techniques in optimizing volatility models, particularly for high-frequency finance data. An empirical study by (Akbar et al., 2023) tested conventional outlier detection methods like Median Absolute Deviation (MADe), Tukey's fences, and standard deviation (SD)-based methodologies, and compared them with GARCH-family models. The claimed that raw outliers in financial time series generate biased estimates of parameters among volatility models, thus reducing the credibility of the forecasts.

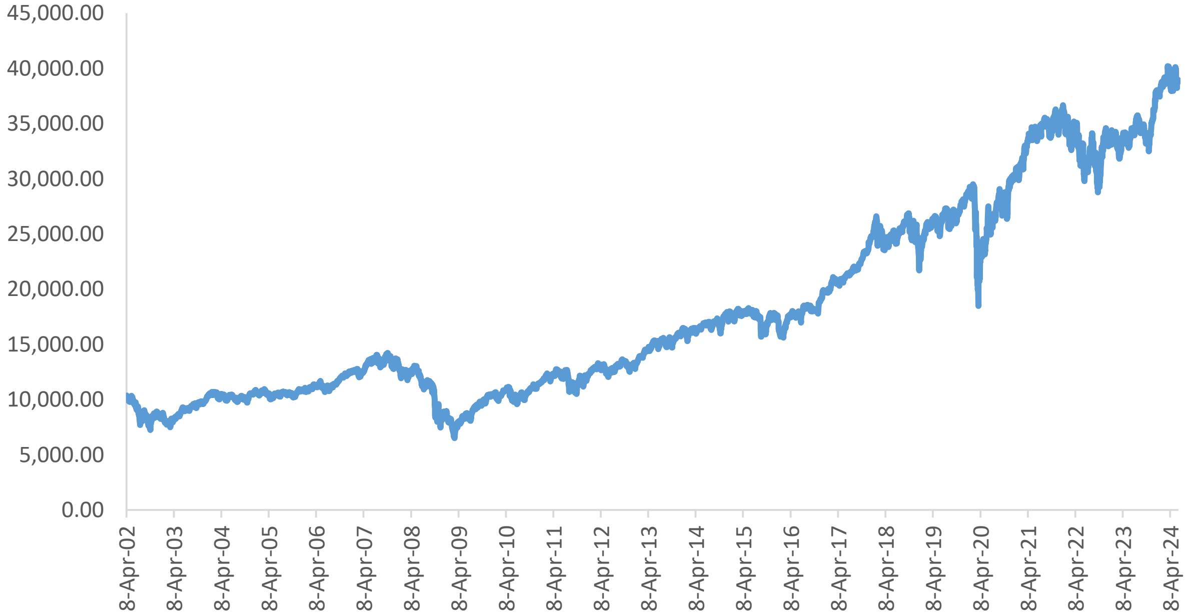
In the last decades the authors have witnessed many works comparing different volatility models and robust estimation methods for the analysis of financial time series. The newer developments have also been focused on hybrid approaches which pair the conventional outlier detection with machine learning techniques. Akbar et al. (2023) in a piece of research utilized six conventional outlier detection methods (standard deviation method, median method, Tukey's methods, MADe method, split sample skewness based boxplot method, and adjusted boxplot method) method to Pakistan stock exchange 100 index data and identified that MADe method performed well in the detection of outliers, while among three GARCH type models (GARCH(1,1), EGARCH and GJR) EGARCH performed well. Similarly, Abid et al. (2024) desaturated that GARCH(1,1) model performs better in the context of forecast performance when return series is adjusted for outliers. Akbar et al. (2024) demonstrated that outliers have dramatic impact on Italian electricity prices by implying different econometric techniques. In the same way using the same econometric methodologies, Waheed et al. (2023) found that outliers are very important to be detected before making forecast using exchange rate data. Further, a similar conclusion was drawn of a study conducted by Studies Khan et al. (2023) in which they explored the effect of petroleum process on food commodity prices. Studies by Kuhe (2022), Andersson & Haglund (2024) and Pasha et al. (2025) confirms the higher efficiency of EGARCH Models, after testing in a normal market environment an asymmetrical response of volatility. Ali (2023), though, compared generally between GARCH models, and concluded that TGARCH model is more suitable in situations where the volatility experiences an abrupt jump, typically during financial crises. From these results, it appears that the model behaviour is closely related to the environment, with EGARCH being the most consistent performer across the seven markets, although TGARCH may be more suitable in turbulent markets. Laurent et al. (2021) provided an interesting balance to this perspective, concluding that, in some instances, simple GARCH models could not be beat by the more advanced Generalized Autoregressive Score framework, suggesting that less can be more. Ané et al. (2017) further advanced volatility modelling through mixed AR(1)-GARCH(1,1) models that have superior performance when compared to pure GARCH specifications.

The problem of outlier sensitivity of financial time series has been answered by Sakata et al. (2016), who also assessed quasi-maximum likelihood estimation against robust approaches. Their theoretical results heavily favour two-stage S-estimators and Hampel estimators over classical procedures, since all the chosen robust methods can at least all but ignore outliers, rather than deleting them altogether, to ensure good reliable parameter estimation. Collectively, these contributions have emphasized various important messages: the effectiveness of the forecasting framework relies not only on the particular aspect or condition of the data (e.g., conditional volatility, extreme events, level of non-linearity or data structure) but also (and most importantly) on the strengths and weaknesses of their interaction, robust estimation is a crucial ingredient when the underlying data generating process is contaminated with outliers and a fertile ground remains open for combining robust estimation methods with other advanced variants of GARCH. Possible extensions could include incorporating machine learning capabilities into GARCH models or creating real-time adaptive forecasting systems where market conditions or the incidence of certain outlier behaviour would be automatically reflected in the forecast. These developments, in the future, could better enhance the robustness and precision of financial time series analysis in academic and application domains.

## 3. Data and Econometric Methodology

This research uses daily returns of Dow Jones Index from April 2002 to June 2024 where the sample period from April 2002 to May 2023 has used for in-sample estimation purpose while the sample period from June 2023 to June 2024 has used for forecasting purpose. Data is retrieved from https://finance.yahoo.com/. The whole sample period pattern is mentioned in Figure 1.

Figure 1: Dow Jones Index Stock Price from April 2002 to June 2024




### 3.1. Outlier Detection Methods

This study uses six different conventional outlier detection methods:

i. 2SD (Two Standard Deviations) Method: This method identifies outliers as observations lying beyond two standard deviations from the mean (i.e. mean ± 2×SD), assuming near-normal distribution. However, it is sensitive to extreme values and non-normal data.

ii. Tukey's Method (IQR-Based): This method uses the interquartile range (IQR) to flag outliers as points below $Q_1$ – 1.5×IQR or above *$Q_3$ + 1.5×IQR* (Tukey, 1977). This method is robust against skewed distributions.

iii. Median Absolute Deviation (MAD) Method: This method defines outliers as values exceeding a threshold (e.g., median ± 2.5×MAD), reducing sensitivity to extreme values (Leys et al., 2013).

iv. MADe (Scaled MAD) Method: This method adjusts MAD by a factor of 1.483 to align with standard deviation in normal distributions; outliers are values beyond median ± *k*×MADe (often *k*=3) (Rousseeuw and Croux, 1993).

v. SSSBB (Small Sample Skewness-Adjusted Boxplot) Method: This method extends Tukey's fences by incorporating skewness adjustments, improving outlier detection in small, asymmetric datasets.

vi. VH (Valentina-Hnétynková) Boxplot Method: This method modifies Tukey's whiskers by skewness-adjusted bounds, enhancing accuracy in both symmetric and skewed distributions (Hubert & Vandervieren, 2008).

### 3.2 Forecasting Methods

Our study uses the following forecasting models,

i. GARCH (Generalized Autoregressive Conditional Heteroskedasticity): GARCH models volatility clustering in financial time series by incorporating lagged squared residuals and past conditional variances (Bollerslev, 1986). It assumes symmetric responses to positive/negative shocks, with the conditional variance equation:

$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$.

Further, GARCH is parsimonious but misses asymmetries present in financial data.

ii. EGARCH (Exponential GARCH): EGACH by Nelson (1991) models asymmetric volatility effects (e.g., leverage effects), where negative shocks increase volatility more than positive shocks. Its logarithmic form ensures positive variance:

$ln(\sigma_t^2) = \omega + \alpha(|z_{t-1}| - E|z_{t-1}|) + \gamma z_{t-1} + \beta ln(\sigma_{t-1}^2)$.

EGARCH's log form avoids parameter restrictions and explicitly models leverage effects.

iii. GJR-GARCH (Glosten-Jagannathan-Runkle, 1993): GJR-GARCH captures asymmetry via a dummy variable for negative shocks:

$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$, where *$I_{t-1}$=1* if $\varepsilon_{t-1}<0$.

GJR directly quantifies how negative shocks amplify volatility more than positive ones.

All three models use maximum likelihood estimation for parameters. EGARCH and GJR outperform GARCH for assets with skewness (e.g., equities). Empirical studies favor EGARCH for flexibility and GJR for intuitive asymmetry modeling (Hansen & Lunde, 2005). Choice of the model depends on data characteristics: GARCH for symmetry, EGARCH/GJR for asymmetric volatility. In our study, we will use all these three models to forecast the returns data.

## Results

This section demonstrate the empirical results obtained using different outlier detection methods and financial time series forecasting models. First, all outlier detection techniques applied on data and average return value replaced instead of detected outlier value corresponding to each outlier detection technique. Second, different GARCH type models used to forecasts all the filtered series obtained after filtering for outliers for the forecasting sample under consideration. Lastly, loss function criteria used to evaluate the performance of each outlier detection technique and forecasting model. A detailed descriptive statistics of given data is mentioned in Table 1.

Table 1: Descriptive Statistics of Dow Jones Index Stock Price from April 2002 to June 2024

| Variable | Observation | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Stock | 5,583 | 18115.39 | 8875.61 | 6528 | 40206 |
| Return | 5,583 | .031 | 1.16 | -11.2624 | 13.59618 |

Table 2 presents Mean Absolute Error (MAE) measures of three forecast models—GARCH, EGARCH, and GJR—executed on financial time series data both without and with outlier removal using various detection techniques. The maximum MAE measures result when outliers are not removed (0.7946 for GARCH, 0.8071 for EGARCH, and 0.8104 for GJR), and they establish the negative influence of outliers on the precision of forecasting. After treating outliers using outlier detection methods, all models exhibit substantial improvement, proving the relevance of outlier handling. Of the methods, the MADe Method is always the best compared to others, producing the lowest MAE for GARCH (0.0368), EGARCH (0.0743), and GJR (0.0717) and thus stands out as the best method of enhancing forecasting accuracy. The other methods like SSSBB, Median, and SD reduce MAE as well but to a lesser extent than MADe, while Tukey and VH Boxplot methods act moderately. For all the situations, GARCH is the best forecasting model, which always yields the lowest MAE, followed by EGARCH and GJR. This is also shown in Figure 2.These findings highlight the significance of handling outliers in financial modeling as well as the effectiveness of the MADe Method in achieving improved forecasting performance, especially when used with GARCH.

Table 2: MAE of GARCH type models with different outlier detection methods

| | GARCH | EGARCH | GJR |
|---|---|---|---|
| With outliers | 0.794584 | 0.807077 | 0.810362 |
| SSSBB | 0.278592 | 0.317061 | 0.317926 |
| Median Method | 0.301016 | 0.336233 | 0.344615 |
| MADe Method | 0.036824 | 0.074288 | 0.071742 |
| SD Method | 0.307876 | 0.34533 | 0.343128 |
| Tukey Method | 0.194342 | 0.232275 | 0.243214 |
| VH Boxplot Method | 0.248485 | 0.273105 | 0.278981 |

Figure 2. MAE Performance of GARCH models for outlier Detection Methods

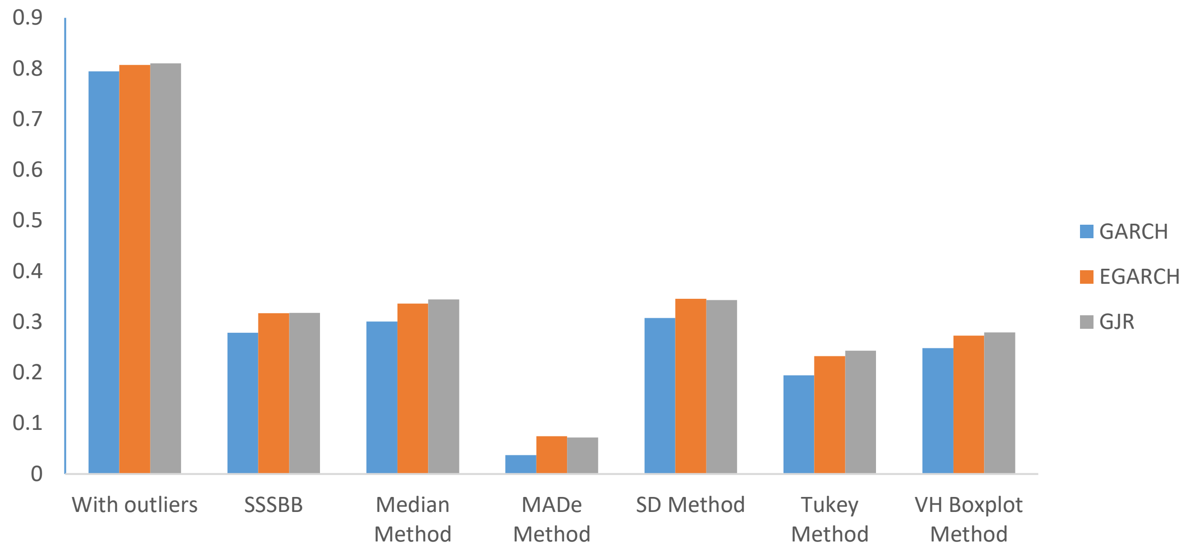



Table 3 indicates forecast performance measures in the form of Mean Absolute Percentage Error Squared Error (MAPE) for three models—GARCH, EGARCH, and GJR—when they are fitted to financial time series data with or without the detection of outliers. With outliers, MAPE values are very large, indicating severe forecasting inaccuracy (175.74 for GARCH, 198.35 for EGARCH, and 196.40 for GJR). It indicates the adverse effect of outliers on model performance. Following the application of various outlier detection methods, substantial improvement is observed with all models.

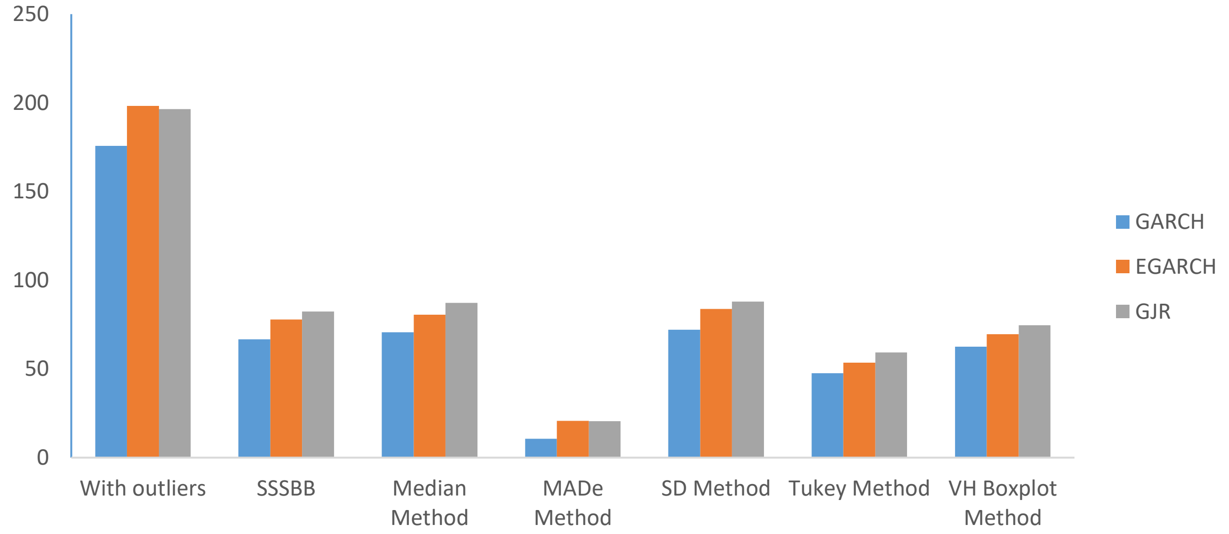
Out of the detection methods, the MADe Method does the best with the minimum MAPE for GARCH (10.56), EGARCH (20.73), and GJR (20.57). It means its effectiveness in eliminating the adverse influence of outliers on financial prediction. The next best among them is Tukey's Method with considerable improvement with lesser MAPE values for all models. Other methods, such as SSSBB, Median, SD, and VH Boxplot, also enhance the precision of forecasts but are less efficient than MADe and Tukey.

In terms of model strength, GARCH is always better than EGARCH and GJR in all situations with the smallest MSE. EGARCH and GJR have merely relatively greater error measurements, yet both drastically minimize their errors after outliers are addressed. These are also shown in Figure 3. The findings underscore the importance of outlier detection and adjustment towards finance prediction, with the MADe Method being particularly effective at accuracy enhancement. These results confirm the utmost significance of the integration of advanced statistical methods and high-level predictive models for the sake of getting precise forecasts in financial time series analysis.

Table 3: MAPE of GARCH type models with different outlier detection methods

| | GARCH | EGARCH | GJR |
|---|---|---|---|
| With outliers | 175.7381 | 198.3489 | 196.404 |
| SSSBB | 66.62275 | 77.85858 | 82.34226 |
| Median Method | 70.65667 | 80.46601 | 87.21394 |
| MADe Method | 10.55793 | 20.72652 | 20.56711 |
| SD Method | 72.03774 | 83.70963 | 87.89587 |
| Tukey Method | 47.52739 | 53.48688 | 59.2539 |
| VH Boxplot Method | 62.42555 | 69.54816 | 74.53434 |

Figure 3. MAPE Performance of GARCH models for outlier Detection Methods




**Conclusion**

The current study tested strictly the impact of outlier detection techniques on GARCH, EGARCH, and GJR model forecasting capability using Dow Jones Index data. Empirical results show that outliers do impair forecasting precision, which is explicitly shown by comparatively much higher MAE and MAPE values in uncorrected data-based models (MAE: 0.7946–0.8104; MAPE: 175.74–198.35). However, the application of outlier detection techniques hugely improved model precision in all versions.

The MADe Method was identified as the optimal treatment for outliers with the lowest error (MAE: 0.0368 for GARCH; MAPE: 10.56 for GARCH) and outperforming other contenders like Tukey's Method and VH Boxplot. Consistency in robustness across every model further cemented its viability for financial time series analysis. The most consistent forecasting model was GARCH with better performance (lowest MAE/MAPE) even in contrast to asymmetric models (EGARCH, GJR) under outlier-adjusted scenarios.

These findings highlight three important implications:

i. Outlier treatment is inevitable to guarantee accurate financial forecasting, as unadjusted anomalies inflate errors by 80–200% in this study.
ii. Method choice is important—MADe's statistical robustness lends itself best to volatility modeling, but less complex methods (Median, SD) are only marginally beneficial.
iii. Model choice interacts with outlier adjustment; GARCH supremacy means that parsimonious models may yield superior results to complex ones given the robust data preprocessing assumption.
For practitioners, these results promote the adoption of a MADe-GARCH pipeline to enhance risk management and trading. Potential follow-up studies could seek to examine hybrid machine-learning strategies in order to further refine outlier detection in non-linear regimes.

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