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Statistical Methods for Measuring Market Risk: Applications in Equity Markets

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Abstract

The importance of measuring market risk lies in assessing the uncertainty in the financial sector, estimating the potential loss, and assisting the investment decision in stock markets. The present review focuses on statistical methods for measuring and forecasting market risk, especially when applied to individual stocks, equity indices and investment portfolios. It includes traditional statistical measures such as standard deviation, historical volatility, beta, alpha, Sharpe ratio and R-squared, as well as risk models such as Value at Risk (VaR), Expected Shortfall (ES) and GARCH. We also consider more sophisticated approaches such as asymmetric volatility models, Extreme Value Theory (EVT) and Filtered Historical Simulation (FHS). The review also addresses practical uses and limitations of these methods, especially their sensitivity to historical data, distributional assumptions and extreme market movements. In general, the combination of complementary statistical approaches may provide a more comprehensive assessment of equity market risk.

Keywords: *Market Risk; Statistical Risk Measurement; Value at Risk (VaR); Equity Market Volatility; Extreme Value Theory (EVT).*

INTRODUCTION

Changes in stock prices can impact the wealth of investors, the performance of their portfolios, and financial stability. Hence market risk is of major concern in equity markets. It deals with the risk of financial loss due to adverse changes in market variables, especially equity prices and returns [1]. Market risk is influenced by a variety of factors such as economic uncertainty, changes in interest rates, inflation, geopolitical events, investor sentiment and changes in market liquidity [2]. Such factors can increase price volatility and lead to conditions of sudden and significant equity market losses. Therefore, accurate measurement of market risk is essential for investors, portfolio managers, financial institutions and regulators to make informed decisions and manage potential losses [3], [4].

Statistics plays an important role in market risk measurement. It estimates the probability and magnitude of adverse market movements using historical returns and probability distributions. Standard deviation and historical volatility are traditional measures of the variability of equity returns. However, such measures may fail to capture extreme losses adequately. This is particularly the case when the return distributions are asymmetric, have heavy tails, or have changing volatility. The Value at Risk (VaR) is a commonly used measure to estimate the maximum expected loss over a period of time with a given confidence level, assuming the model assumptions are met [5]. Expected shortfall (ES) goes one step further by estimating the average loss above the VaR level, giving more information about losses in periods of extreme market conditions [6]. In addition, volatility models such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model are able to model the time-varying fluctuations of equity returns and enhance risk forecasting [7].

Although these methods are available, their accuracy depends on model assumptions, data quality and market conditions. This review presents the main statistical methods to measure market risk in equity markets, paying special attention to traditional risk measures, VaR and ES estimation methods, and sophisticated volatility and extreme-risk models. It also explores how they can be applied in practice, and their relative strengths and weaknesses in identifying and predicting possible equity market losses.

STATISTICAL MEASURES AND MODELS FOR EQUITY MARKET RISK

Statistical measures and risk models are important for measuring equity return volatility, measuring investment performance and estimating potential financial losses. These techniques foster an understanding of the correlation between investment risk and market movements among portfolio managers and investors [8]. Volatility, systematic risk, and risk-adjusted returns are all described using core statistical measures. In both normal and extreme scenarios, advanced risk models assess potential losses and analyze market behavior [9].

Core Statistical Measures

The following measures are commonly used to analyse equity market risk and investment performance:

1. Standard Deviation/Historical Volatility: The standard deviation is a way to measure how much the returns on a stock vary from the average. Historical volatility is the degree to which the returns have varied over a period of time. Generally the higher these figures are the greater the price uncertainty and risk [10].

2. Beta (β): Beta measures the price sensitivity of a stock to the movements of the wider market. A beta greater than 1 means that the stock is more sensitive to market swings and a beta less than 1 means that the stock is less sensitive to market swings.

3. Alpha (α): Alpha is the excess return of an investment over the benchmark return or asset-pricing model. A positive alpha means that the return was higher than what was expected by the model given the risk factors.

4. Sharpe Ratio: The excess return per unit of total volatility of the investment is quantified by this ratio. This is contingent upon the distribution of returns and the period of investment, but a higher Sharpe ratio is generally regarded as indicating superior risk-adjusted performance .

5. R-squared (R^2): R-squared is a measure of how much of the variation in a stock's returns can be explained by a regression model, such as the market benchmark model. Higher value is better statistical fit but does not necessarily mean less investment risk.

Risk Models

Risk models try to estimate potential losses, capture changing volatility, and evaluate adverse market conditions beyond basic statistical measures. Their performance depends on the quality of the data, the assumptions made in the model and the ability to capture extreme market moves [11].

1. Value at Risk (VaR): Value at risk (VaR) measures the potential loss of a portfolio over a specific time horizon at a given confidence level. The major approaches for estimating are historical simulation, variance-covariance analysis, and Monte Carlo simulation.

2. Expected Shortfall (ES): ES estimates the average loss in the tail of the loss distribution beyond the VaR cut-off point. It provides more information about the severity of losses in extreme market conditions.

3. GARCH Models: Generalized Autoregressive Conditional Heteroskedasticity models utilize past returns and past volatility estimates to estimate time-varying volatility. They are useful for detecting volatility clustering in equity markets and forecasting changing risk levels.

4. Extreme Value Theory (EVT): EVT focuses on the tail ends of return distributions to estimate the likelihood and magnitude of extreme market losses. This is especially true when the extreme observations are not well represented by conventional models [12].

5. Stress Testing and Scenario Analysis: These methods project losses into portfolios in stressed market environments, such as sudden stock price drops or volatility spikes, hypothetical or based on past events. They complement statistical estimates of risk by looking at scenarios that may be underrepresented in the historical data [13].

ADVANCED STATISTICAL METHODS FOR VOLATILITY AND EXTREME RISK ESTIMATION

Equity market returns are often characterized by volatility clustering, asymmetric responses to market news and occasional extreme losses that cannot be adequately captured by simple statistical measures. Such characteristics are explained by sophisticated statistical techniques that capture the evolving nature of volatility and assign probabilities to extreme market events. These approaches can help improve risk forecasting, assess portfolio exposure and provide insights into market behavior in periods of financial uncertainty [14]. The main approaches are ARCH and GARCH models, asymmetric volatility models, Extreme Value Theory (EVT) and Filtered Historical Simulation (FHS).

1. ARCH and GARCH Models: The ARCH model estimates the current volatility from past squared return shocks, while the GARCH model also uses the previous estimates of the conditional variance. These models capture the clustering of volatility where high volatility is usually followed by high volatility which makes them useful for forecasting changing equity market risk.

2. Asymmetric Volatility Models (EGARCH and GJR-GARCH): The diversity in volatility responses to positive and negative returns may not be adequately captured by con-

ventional GARCH models. Exponential GARCH (EGARCH) and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) are the methods that capture the asymmetry. They are especially significant in equity markets, where negative returns can exacerbate volatility more than positive returns of the same magnitude [1].

3. Extreme Value Theory (EVT): The tail behavior of return or loss distributions is of interest to EVT because it enables the estimation of the probability and severity of rare, extreme market losses. Peaks-over-Threshold and similar methods are useful in estimating tail risk beyond the normal market movements, but the estimates are sensitive to the choice of threshold and the number of extreme observations.

4. Filtered Historical Simulation (FHS): FHS combines historical return information with volatility modeling. The estimated conditional volatility is used to standardize the returns and the residuals are resampled to generate possible future returns using the forecasted volatility. This approach captures the time-varying market volatility and preserves important aspects of the empirical return distribution and allows for more flexible VaR and ES estimation.

APPLICATIONS AND LIMITATIONS IN EQUITY MARKETS

Statistical risk measures and models are widely used in equity markets to evaluate investment risk, estimate potential losses and support investment portfolio management decisions. They are used depending on whether the analysis is of individual securities, wider market indices or diversified investment portfolios." Volatility, beta, Value at Risk (VaR) and Expected Shortfall (ES) are measures that provide complementary information on market sensitivity, variability of returns and potential losses. But their reliability depends on the chosen model, data quality and present market conditions [15].

Applications of Statistical Risk Measures

Individual Stocks: Volatility and beta help assess price fluctuations and sensitivity to overall market movements, supporting stock selection and investment decisions.

Equity Indices: VaR, ES, and GARCH models help estimate potential index losses and forecast changing volatility during periods of market uncertainty.

Investment Portfolios: Portfolio-level VaR, ES, and stress testing help assess aggregate exposure, evaluate diversification benefits, and identify potential losses under adverse market conditions.

Table 1: Applications of Statistical Risk Measures in Equity Markets

Application area	Statistical methods	Main purpose
Individual stocks	Volatility, beta, alpha	Assess price variability, market sensitivity, and relative performance
Equity indices	GARCH, VaR, EVT	Forecast volatility and estimate potential market losses
Investment portfolios	VaR, ES, stress testing	Evaluate aggregate risk and potential losses under adverse scenarios

Limitations of Statistical Risk Methods

There are a number of limitations to statistical risk methods that may affect the accuracy of equity market risk estimates. If returns are fat-tailed or asymmetric, then normal distribution models may understate the risk. VaR is unable to capture the extent of losses above its specified limit, but the choice of extreme observations and thresholds can affect the estimations obtained by EVT. Also, methods that rely heavily on historical data might not catch structural changes, financial crises or unprecedented market events. There is also still some uncertainty in the forecasts as volatility patterns and market relationships can change over time. Therefore, combining the backtesting and stress testing with the complementary risk measures can provide a more comprehensive evaluation of the risk of equity markets [16].

LITERATURE REVIEW

(Astaíza-Gómez, 2025)[17] focused on "foreign investment, CDS spreads, exchange rates and stock return volatility" and it aimed to assess the effect of uncertainty and global risk on financial markets in emerging countries. By using structural vector autoregression (VAR) models and more than 8.6 million ticker transaction data, the study found that increases in Economic Policy Uncertainty (EPU) significantly reduce "foreign net buys, more than global market volatility (VIX)". Global volatility drives CDS spreads but they also impact exchange rates which leads to currency depreciation. The results provide insights that can help control risk in opaque markets and improve financial stability by highlighting the links between uncertainty, global risk and market instability.

(Assa, 2025)[18] introduces the idea of static risk measures as a risk assessment tool for assessing the severity of loss in a frequency-severity framework with common and systemat-

ic shocks. In this article we discuss several important properties of static risk measures and compare them to ruin-based risk measures. Furthermore, the consequences of a strong representation of static risk measures for the construction of the best possible reinsurance contracts will be discussed. The introduced flexibility allows the model to include new features such as systematic and common shocks, which improve its applicability to the reinsurance sector.

(Jareño et al., 2025) [19] analyzes the stock markets' reaction to the changes in international risk factors at different market phases during the COVID-19 pandemic. We apply the quantile regression approach to data from seven countries severely affected by the sanitary crisis between January 2020 and December 2021 in an effort to identify the different sensitivities to risk sources depending on the market being bullish or bearish. Our results show a stronger explanatory capacity at extreme quantiles and significant differences in sensitivities found to be depending on the nation, the market circumstances and the specific risk factor.

(Lukitosari et al., 2025) [20] uses the GARCH-MIDAS model to analyze the volatility of the Indonesian composite index (ICI) by combining daily ICI returns with monthly macroeconomic indicators such as "inflation rate (IR), consumer price index (CPI), effective federal fund rate (EFFR), and Indonesian bank interest rates (BIIR)".Compared to prior studies our results suggest that the EFFR has the strongest impact on ICI volatility. "Mean squared error (MSE) and mean absolute error (MAE)" evaluate the effectiveness of forecasting, showing the improved predictive power of the EFFR variable. The value at risk (VaR) of the ICI is used for risk assessment and the EFFR is used to control for macroeconomic influences on market volatility. The VaR values at the 99% and 95% confidence levels help in understanding the maximum possible loss and thus help to make better investment decisions. The investigation enhances comprehension of the correlation between volatility in the stock market and macroeconomic variables. This research offers crucial insights for investors and decision-makers to optimize their investment strategies and mitigate risk in the Indonesian equity market.

(Demirdöğen, 2024) [21] In this study, a portfolio was formed by using stocks of four main banks in BIST30 (AKBNK, GARAN, ISCTR and YKBNK) with Random Forest and Monte Carlo simulation. Three different "Value at Risk (VaR approaches (historical, parametric and Monte Carlo) were used to provide predictions with the previous four periods. "VIX (fear index), USD/TL, Gold/TL, and Brent/TL" were used as independent variables. The relevance of the variables was explored by employing machine learning regularization techniques including ridge, lasso and elastic net regression models. Again, the Random Forest was used to analyze the impact of independent variables on the stock weights. For each VaR model, the realized VaR results were compared with the stock weight distributions in the previous four periods. The results show that the historical VaR technique gives the closest result for the other three periods and the parametric VaR method gives the best result for the first period. The results were found to be more optimistic than the actual results. Even the closest results were not even within 30% of the actual number. The gap may be bigger than expected due to the decrease in the value of the bank stocks over the last two years and the big fluctuations in the stock market over the last 4 periods regardless of the individual companies involved.

(Wu, 2023) [22] The objective of this paper was to resolve the decision problem with respect to project portfolios by employing "statistical risk analysis and Value at Risk (VaR)". When it comes to new product development (NPD), traditional economic evaluation criteria employed in project portfolio management are predicated on the idea that precise estimates would not change over time. However, given the inherent volatility of NPD initiatives, it is obviously impossible to assume that NPD remains static. In this paper, we emphasize how important uncertainty is while choosing NPD portfolios and explain why it should not be disregarded. In the evaluation and prioritization of NPD portfolios, we demonstrate the critical role of uncertainty through the use of Value at Risk measurements. Academics and practitioners are given the study's implications for statistically modeling NPD portfolio choices.

(Chakraborty et al., 2021) [23] This study offers an assessment of the empirical and methodological developments in the measurement of severe market risk. The "value at risk (VaR) and VaR-based" alternative anticipated shortfall (ES) were then determined to be the primary measures of severe market risk by this evaluation. The shortcomings of conventional modeling methodologies for VaR-ES measures have resulted in the development of numerous sophisticated estimation methodologies. However, regulatory arbitrage and other inconsistencies are encouraged by the absence of an ideal methodology under the internal models approach (IMA) regime, where financial institutions (FIs) can select an appropriate VaR-ES modeling technique. Thus, the theoretical and empirical research literature on VaR and ES estimate for financial asset market prices is examined in this work. This study concludes that the filtered historical simulation (FHS) and extreme value theory (EVT) are very realistic approaches. Furthermore, appropriate VaR and ES measures are provided by mixture distributions, asymmetric and nonlinear variants of the conditional quantile (CQ) method, (volatility) asymmetry, and long memory conditional volatility models, particularly those that assume skewed and leptokurtic distributions.

(Zhu, 2019) [24] The primary goal of investing in securities is to get rewards. Many investors buy in a variety of assets at the same time in order to diversify risks and maximize rewards. The two main problems facing the financial industry are risk measurement methods and portfolio models. In this work, Markowitz risk compensation model, Arrow-Pratt risk compensation model and Jia & Dyer standard risk model are studied including the calculation method and applicable condition. This paper presents the mean entropy optimized investment model and the transaction cost portfolio model. Empirical analysis shows that it is suitable for calculating the return and risk of a portfolio. The model predicts that diverse investing strategies will result from investors' varying degrees of risk avoidance.

DISCUSSION

The literature reviewed emphasizes the significance of statistical methods in the measurement and management of market risk in equity markets. Standard deviation, beta and Sharpe ratio are traditional measures that inform about return variability, systematic risk and investment performance. But these measures may not fully capture evolving volatilities and extreme market losses. VaR and ES are important methods to estimate possible financial losses. GARCH models can help to detect the volatility clustering and improve the risk forecasting. The results of Chakraborty et al. (2021) also show that EVT and Filtered Historical Simulation are good methods for extreme market risk estimation. Likewise, Jareño et al. (2025) and Lukitosari et al. (2025) state that market risk and volatility are affected by the dynamics of market conditions and macroeconomic factors. However, historical data, distributional assumptions and forecasting uncertainty still impact on the accuracy of statistical models. Thus, combining conventional risk measures with more sophisticated volatility and extreme risk models may result in a more reliable assessment of equity market risk.

CONCLUSION

Equity markets rely on statistical methods to measure, analyze and manage market risk. Traditional measures like standard deviation, beta, alpha, and the Sharpe ratio are used to assess the variability of returns, sensitivity to the market, and the effectiveness of the investment. However sophisticated methods like VaR, ES, GARCH, EVT and FHS provide additional capabilities of estimating possible losses, modeling changing volatility and identifying extreme market events. The studies reviewed suggest that no single statistical method is adequate to capture all dimensions of equity market risk. Their effectiveness depends on market conditions, properties of data and assumptions of the underlying model. In addition, historical data limitations and unexpected market shocks can affect the accuracy of forecasts. Therefore, a combined approach, including traditional statistical measures, advanced risk models, backtesting, and stress testing, is important for a complete risk assessment. This approach helps to make better decisions for investment, portfolio management and financial risk management under changing equity market conditions.

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