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Optimizing Value at Risk and Forecasting Financial Trends Using Taguchi L16 Method and Linear Trend Analysis: A Study Across Multiple Companies

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Abstract: In order to maximize Value at Risk (VaR) and predict future financial trends for four companies—Apple, Coca-Cola, Amazon, and McDonald's—this study combines statistical methods, a basic linear trend model, and the Taguchi L16 method. The Taguchi orthogonal array was used to analyze the impact of three important parameters on VaR at four levels: mean return (μ), standard deviation σ, and stock price (S_t). The most important parameters were found, their impacts were ranked, and their interactions were investigated using analysis of variance (ANOVA) and analysis of means (ANOM). After that, historical data was subjected to a basic linear trend model in order to forecast future VaR behavior. Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were used to validate the correctness of the model. The findings provide a solid framework that blends experimental design and predictive modeling for data-driven financial decision-making, exposing the key factors influencing VaR and providing insights into future risk trajectories.

Keywords: Value at Risk, ANOM, ANOVA, Regression coefficient, Linear Trend Model, future predication

1 Introduction

Risk is the possibility that an investment's actual return will fall short of its expected return. The degree of uncertainty regarding the future return is another way to define it. There are numerous ways to reduce future risk, including: probability of default [1], credit default risk [2], loss given default [3], value at risk (VaR) [4] etc.
Increased trading in securities, cash instruments, and new financing opportunities have led to a rise in complex financial instruments like derivatives used to manage market risks, as well as high volatility in exchange rates, interest rates, and commodity prices. These factors have increased the need for VaR over the past few decades, resulting in portfolios that contain many cash and derivative instruments, many of which have unclear risks. As a result, there is a need for a straightforward, quantitative metric to evaluate market risk at the portfolio level.
The most straightforward technique for determining VaR is historical simulation. It operates by examining the changes in market variables (such as rates or prices) over the previous periods, which are typically days, and applying those changes to the present portfolio. Based on historical market movements, this generates N fictitious portfolio values. A distribution of possible gains and losses is constructed using these values. A clear indicator of possible risk is provided by VaR, which is the loss value that is exceeded just a tiny proportion of the time (for example, 5 percent) [5].
For financial institutions, measuring risk is an essential duty. One useful strategy in the context of market risk is to estimate the possible losses that can transpire in the event that the value of the assets in the portfolio drops.

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VaR is specifically designed to achieve this goal. VaR measures the highest possible loss that investor, with a certain degree of confidence, might sustain over a particular period of time [6].
According to Jorion (2001), VaR is the greatest predicted loss at a certain confidence level over a given time period under normal market conditions. For instance, a bank may claim that, at a 99 percent confidence level, the daily VaR of its trading portfolio is 1 million. This indicates that there is a mere 1 percent risk that the daily loss will surpass 1 million in a typical market. VaR is essentially the maximum loss expected in the absence of severe adverse occurrences [7].
To achieve the study's objectives, a structured methodology was implemented, integrating experimental design, statistical modeling, and risk measurement techniques. The Taguchi L16 orthogonal array and a simple linear trend model were employed to identify the most influential factors affecting the response variable and to forecast the future trajectory of VaR for four major companies: Apple, Coca-Cola, Amazon, and McDonald's. Key variables— mean of return , standard deviation of return , and stock price (were derived from historical price data and used to compute VaR, representing each firm's market risk threshold.
While VaR has been widely studied using traditional econometric and simulation-based models, this study is one of the first to integrate the Taguchi L16 orthogonal array in VaR to optimize and a trend forecasting model for project future risk exposure. This hybrid statistical-experimental approach provides a structured and efficient methodology for screening key drivers of financial risk before applying more complex or computationally intensive models. The objective of this study is to evaluate the impact of different factor levels on VaR and to identify the conditions under which VaR reaches its highest value, in order to help organizations better understand and prepare for worst-case market risk scenarios.
To combat problems related to identifying primary causes of financial risk and estimating VaR, in this paper, we integrate a systematic experimental design approach, statistical testing, and time series modeling. Specifically, we employ the Taguchi L16 orthogonal array to effectively search for an understanding of various variables on VaR with the lowest number of experimental runs. For statistical testing for determining the percentage each factor contributes to the response variable, we apply ANOVA [8]. We also employ the ANOM [9]—a graphical technique that is an adjunct to ANOM—to identify desirable levels for each factor and visually identify their impact on VaR. Lastly, we apply a linear trend model to extend future VaR values forward according to previously established trends, understanding long-horizon risk behavior under the assumption of stable directional change in the future.

2 Methodology

The optimization in this study is based on identifying the parameter combinations that result in the highest VaR, aligning with the risk assessment objective of highlighting maximum potential loss conditions under normal market fluctuations. This study aims to analyze the impact of different parameters on a response variable and predict future trends for four companies using the Taguchi L16 method and a simple linear trend model. The data have being collected from the www.yahoofinance.com of the four companies from the period 29th Sep 2019 to 22nd Sep 2024. To estimate the parameters of VaR, we utilized historical stock prices. From this data, the mean (μ) and standard deviation (σ) were calculated for all the firms. These computed values served as the levels for the factors in the Taguchi method, forming the basis for the experimental design and analysis. The return r_t at time t is defined as:

$$r_t = \ln(\frac{S_t}{S_{t-1}})$$

where S_t is the closing price at time t. These returns are then used to estimate the mean (μ) and standard deviation (σ), which form the inputs for VaR estimation. Using the three parameters S_t, μ, and σ we can calculate the VaR using the formula:

$$VaR = (Z \times \sigma + \mu) \times S_t$$

In order to estimate VaR, we start by finding value t, where

$$P(X < t) = \alpha$$

Where $X \sim N(\mu, \sigma^2)$: X is a random variable
Standardizing gives:

$$P\left(Z < \frac{t-\mu}{\sigma}\right) = \alpha$$

$$N\left(\frac{t-\mu}{\sigma}\right) = \alpha$$

Let us take $\alpha = 0.025$, it means confidence level is 97.5%. The above equation becomes

$$N\left(\frac{t-\mu}{\sigma}\right) = 0.025$$

Note: $N(-1.96) = 0.025$ (Normal Distribution Table)
So,

$$N\left(\frac{t-\mu}{\sigma}\right) = N(-1.96)$$

$$\frac{t-\mu}{\sigma} = -1.96$$

$$t = -1.96 \cdot \sigma + \mu$$

Since t is a percentage investment return per period, the 97.5% VaR over one period on stock price portfolio is $t \times S_t$, this means that we are 97.5% certain that an investor will not lose more than $t \times S_t$ over the next period (if t is negative) and if t is positive, then it means an investor will not gain more than $t \times S_t$ over the next period. The returns are used to estimate the mean and standard deviation, which form the inputs for VaR estimation.

The methodology is structured as follows:

2.1 Design of Experiment Using Taguchi L16

The effects of three factors,S_t, μ and σ each at four levels on the response variable, have been studied using the Taguchi L16 orthogonal array design. This design allows the effective study of the main effects and interactions between factors with a minimum number of experiments. Each of the experiments was conducted under the conditions predefined by the Taguchi L16 array. The L16(4^3) orthogonal array was selected because the study involves three factors, each evaluated at four levels. This configuration matches the L16 design structure, ensuring efficiency while maintaining orthogonality [10,11,12].
This study includes three independent factors: S_t, μ and σ each examined at four levels. These levels were derived from historical stock data representing distinct ranges across four companies (Apple, Coca-Cola, Amazon, and McDonald's). These factors were selected based on their direct mathematical contribution to VaR estimation and their relevance in standard financial risk modeling frameworks. Stock Price represents exposure, Mean Return reflects expected performance, and Standard Deviation captures volatility. Given three factors, each at four levels, the L16(4^3) orthogonal array was chosen for its efficiency in estimating main effects and interactions with a minimal number of experimental runs (16), while maintaining orthogonality [10].

2.2 ANOVA-Statistical Analysis of Variance

The technique of ANOM and ANOVA was used to discern which factors have a significant influence on the response variable. Full computation of F-statistics with associated P-values for all factors was carried out to establish the level of significance among them. The ranking of these factors in order of their influences on the response variable will be done based on values of delta and main effects plots.

2.3 Simple Linear Trend Model

A simple linear trend model is used to predict the future performance of the response variable concerning four firms. Historic trend data of each firm had been analyzed to obtain relationships representing the variation of the respondent variable linearly against time. Such model parameter estimation provided the required bases for necessary extrapolations and thus helped further toward future predictions.

2.4 Error Matrix Analysis

To justify the prediction accuracy of the simple linear trend model, error metrics such as MAE, MSE, and RMSE have been calculated for each company. These were compared to identify the company with a promising future trend based on minimum error values.

2.5 Integration of Taguchi and Statistical Tools

The results obtained from the Taguchi method were integrated with statistical tools to identify the most impactful factors with respect to the response variable. Main effects and interactions for the factors were thus evaluated to elaborate comprehensively in terms of their causes.

2.6 Comparison and Insights

Finally, the results of the Taguchi analysis and trend predictions were compared for the four companies. Inferences have been drawn on which parameters have the most significant impact on the response variable and which company shows the best future trend based on the error metrics.
This methodology allows one to understand, in a systematic way, the effects of factors on the response variable, besides forecasting trends for decision-making and optimization.

2.7 Taguchi Design

L16(4^3) is a part of the orthogonal array L16(4), in which there will be 3 factors, all tested at 4 levels over 16 experimental runs. L16(4^3) would select columns from L16(4) in a way that maintains the balance and orthogonality of the experiment. In all, 4 levels for each factor were obtained as shown in Table 1. The correspondent stock prices are the following companies: Apple, Coca-Cola, Amazon, and MC Donald's. These provide the observed data for the definition of the factor levels so that the analysis of these factors' effects on the response variable will be possible in an efficient and robust manner.

Table 1: Observed Data

Factors	1	2	3	4
S_t	71.39	190.33	227.48	302.99
μ	0.0015	0.0018	0.004	0.006
σ	0.0303	0.0311	0.04	0.045

Table 2: Experimental Runs and VaR Estimates Based on Taguchi L16 Design

Stock Price S_t	Mean μ	SD σ	VaR
71.39	0.0015	0.0303	195.323
71.39	0.0018	0.0311	196.8365
71.39	0.004	0.04	229.5902
71.39	0.006	0.045	237.3004
190.33	0.0015	0.0311	535.9693
190.33	0.0018	0.0303	509.5515
190.33	0.004	0.045	707.2663
190.33	0.006	0.04	537.4919
227.48	0.0015	0.04	843.0409
227.48	0.0018	0.045	943.4051
227.48	0.004	0.0303	510.9201
227.48	0.006	0.0311	439.9463
302.99	0.0015	0.045	1274.376
302.99	0.0018	0.04	1105.065
302.99	0.004	0.0311	704.7547
302.99	0.006	0.0303	561.7435

3 Result and Analysis

The Taguchi L16 method is then employed to evaluate the output (VaR) for each combination of factors and levels as per the L16(4^3) orthogonal array. Using the Taguchi L16(4^3) orthogonal array, the experiment evaluates the outputs for various combinations of the three factors (, and) across their four levels. The results are presented in Table 2, which captures the L16 design and the corresponding output values for each experimental run. This systematic approach allows for efficient analysis of factor interactions and their impact on the response variable, enabling insights into the optimal configuration for risk management.

4 Analysis

The outputs of the regression analysis shown in Table 3 contain Coef., SE Coef, T, and P for predictors. Thus, the constant term had a coefficient of -28.01 with a very high standard error of 87.47, which gives it a t-value of -0.32 and a p-value of 0.754 and hence is insignificant. S_t has a coefficient of 220.19, standard error of 19.56, t-value of 11.26, and p-value of 0.000, making it highly significant. Similarly, μ has a coefficient of -95.48, standard error of 19.56, t-value of -4.88, and p-value of 0.000, hence strongly significant. Last but not least, *sigma* shows a coefficient of 124.80, standard error of 19.56, t-value of 6.38, and p-value of 0.000, making it significant in the model.

Table 3: Estimated Model Coefficients

Predictor	Coef	SE Coef	T	F
Constant	-28.01	87.47	-0.32	0.754
S_t	220.19	19.56	11.26	0.00
μ	-95.48	19.56	-4.88	0.00
σ	124.80	19.56	6.38	0.00

Table 4: Model Summary

S	R-Sq	R-Sq(adj)
0.4733	99.14%	97.84%

This model has a very good fit; this is manifested by the very high R^2 and adj R^2 , with a low standard error as shown in Table 4. This shows that the model is very efficient in describing the variability of the data and giving predictions on the same. High R^2 and adj R^2 : The predictors account for almost all the variability in the response variable, which represents a strong model. The slight decrease from R^2 to adj R^2 is just the adjustment for model complexity. Small Standard Error (SS): This small value reflects that the predictions made by the model are close to the actual observed values.

4.1 Normality

The residual Figure 1 below shows that the data meet normality and stationarity assumptions. In the normal probability plot, the residuals fall approximately along a straight line; thus, the distribution of the residuals is close to normality. Moreover, this is supported by the histogram with a distribution of the residuals being roughly symmetric, hump-shaped, with most points lying near the center. The plot of residuals against fits shows no pattern whatsoever; this is indicative of variance constancy and hence heteroscedasticity could be avoided. Besides, the residuals versus order plot shows random fluctuations around zero with no observable trends, which means stationarity. Overall, residuals are well-behaved since both normality and stationarity assumptions are met.

4.2 ANOVA

The ANOVA Table 5 shows the contribution of each factor—St, Mean, and SD—to the response variable's variability. Each of these factors has an associated sequential sum of squares (Seq SS), which quantifies its unique contribution to the total variability, and an adjusted mean square (Adj MS), representing the average variability per degree of freedom (DF). The significance of each factor is determined by the F-statistic, which compares its variance with the residual error variance.

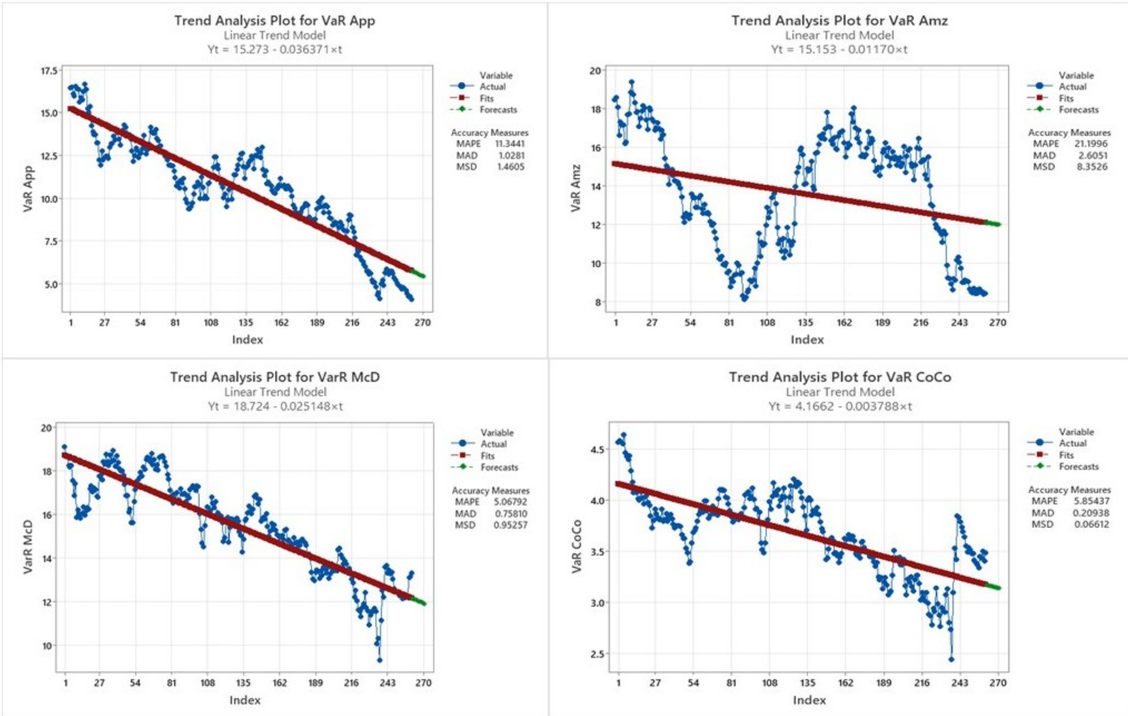

Fig. 1: Normality

It can be seen that St explains the maximum amount of variability (Seq SS = 101.289), followed by SD (Seq SS = 33.496) and Mean (Seq SS = 19.404). All three factors are highly significant with P¡0.05, confirming that they make meaningful contributions to the response. Correspondingly, the residual error is small (Seq SS = 1.344), which reflects the model's strength in effectively capturing the variation within the data.

Lastly, the model indicates that St has the strongest influence, while SD and Mean also play significant roles. The minimal unexplained variance ensures a good fit of the model. The regression Table 3 and Table 4 and

Table 5: ANOVA Table Summary

Source	DF	Seq SS	Adj SS	Adj MS	P
S_t	3	101.289	101.289	33.7631	0.000
μ	3	19.404	19.404	6.4679	0.001
σ	3	33.496	33.496	11.1653	0.000
Residual	6	1.344	1.344	0.2240	
Total	15	155.533			

ANOVA Table 5 results jointly reinforce the significance of the same factors influencing VaR. Both analyses identify stock price, standard deviation, and mean return as significant predictors, with S_t contributing the highest variance (Seq SS= 101.289; ¡ p¡0.001) and the largest regression coefficient ($\beta = 220.19$). This alignment between the regression coefficients and ANOVA F-statistics confirms that S_t exerts the strongest positive effect on VaR, followed by *sigma* and μ. The high R^2 (99.14 percent) from the regression model further supports the explanatory strength indicated by the ANOVA results. Hence, the combined interpretation demonstrates model robustness and internal consistency, showing that both methods converge in identifying S_t as the dominant determinant of financial risk.

4.3 ANOM

A response Table 6 for means reports the effects of the different levels of the factors St, Mean, and SD on the response variable. The three factors each have four levels, and the mean value of the response variable is calculated for each level. For St, with a response range between Level 1 (2.148) and Level 4 (9.115), St has the most impact, as suggested by a high delta value of 6.967. Delta values represent the difference between the response values at the extremes of a variable's range, measuring the magnitude of change.

For Mean, the response values decrease from 7.122 at Level 1 to 4.441 at Level 4, with a rather small delta value of 2.681, indicating that the effect on the response was

Table 6: Response Table for Means

Level	Stock Price	Mean	SD
1	2.148	7.122	4.444
2	5.726	6.887	4.694
3	6.843	5.381	6.788
4	9.115	4.441	7.906
Delta	6.967	2.681	3.462
Rank	1	3	2

moderate. SD shows a more varied pattern, ranging from 4.444 at Level 1 to 7.906 at Level 4, with a delta of 3.462, ranking second in magnitude.
The rank column prioritizes the factors based on their respective delta, indicating that St is the most influential, followed by SD, while Mean has the least impact. Overall, St drives the response most significantly, while Mean has the least effect.
Optimal Combination: The factors that provide the maximum value of VaR are the maximum values of St and SD and the minimum value of Mean.

This Figure 2 illustrates how the factors St, Mean, and SD influence the response variable by displaying the mean response values at each level of these factors. St: The graph shows a clear upward trend, with the mean response increasing significantly from 71.39 to 302.99. This indicates that as the level of St rises, its effect on the response variable becomes stronger. This observation aligns with earlier analyses identifying St as the most influential factor. Mean: The plot exhibits a slight but consistent downward trend as levels increase from 0.0015 to 0.0060, suggesting a decreasing impact of Mean on the response variable. The smaller variations indicate that Mean has a comparatively less significant effect than St. SD: The graph reveals an upward trend from 0.0303 to 0.0450, showing a noticeable rise in the response. While not as pronounced as St, SD demonstrates a stronger effect compared to Mean. St has the strongest influence on the response variable, followed by SD, with Mean having the least effect.

4.4 Normality and stationarity

Residual plots of Figure 3 do not indicate any violation of normality and stationarity assumptions in the data. The normal probability plot shows residuals falling along a straight line, indicating that the residuals have a normal distribution. The residuals versus fits plot shows no discernible patterns, suggesting constant variance and the absence of heteroscedasticity. Overall, the well-behaved residuals confirm that normality and stationarity assumptions are satisfied.

4.5 Linear Trend Model

The methodology involves analyzing 261 observations of VaR data for four companies to forecast future values of VaR through a simple linear trend model. The model assumes trend continuity and evaluates accuracy using MAPE, MAD, and MSD metrics. These measures help gauge the model's predictive performance and applicability to each firm by comparing the calculated accuracy metrics across companies. The company with the lowest error values is considered most aligned with the assumptions of the linear trend model, providing a more reliable basis for forecasts to aid in decision-making. Figure 4 presents the trend analysis plots of VaR using the linear trend model for the four companies—App, Amz, McD, and CoCo. All plots show a general negative trend over time, with decreasing VaR values, supported by the negative coefficients of tt in their respective equations. The accuracy measures—MAPE, MAD, and MSD—differ across the companies. McD and CoCo have relatively lower error values compared to App and Amz, indicating better model fits for these companies. The plots display actual data points (blue), fitted trends (red), and forecasted values (green), illustrating the models' ability to capture the overall downward trends in the data despite some variability in the actual observations. Fitted Trend Equation
$y_t = 15.273 - 0.036371t(App)$
$y_t = 15.153 - 0.01170t(Amz)$
$y_t = 18.724 - 0.025148t(MCD)$
$y_t = 4.1662 - 0.0037881t(CoCo)$
The fitted trend equations for the VaR of the four companies reveal differences in initial risk levels and rates of decline over time. McD has the highest initial VaR (18.724), followed by App (15.273), Amz (15.153), and CoCo (4.1662), indicating varying degrees of initial risk exposure. Regarding the rate of decline, App shows the steepest decrease (0.036371), followed by McD (0.025148), Amz (0.01170), and CoCo (0.003788). This suggests that App is the most aggressive in reducing its risk exposure, while CoCo demonstrates a slower and more stable decline. These trends reflect distinct risk profiles and reduction strategies: App aggressively lowers its risk, McD and Amz adopt moderate approaches, and CoCo maintains minimal reductions over time, reflecting a more stable strategy.

4.6 Forecast

The forecasted VaR values for the four companies—App, Amz, McD, and CoCo—demonstrate a consistent downward trend over time, aligning with their respective fitted linear trend model as shown in Table 7. App exhibits the steepest decline, with forecasts dropping from 5.74 to 5.42, reflecting an aggressive risk reduction strategy. Amz shows a slower rate of decline, indicating a gradual decrease in risk exposure. McD maintains

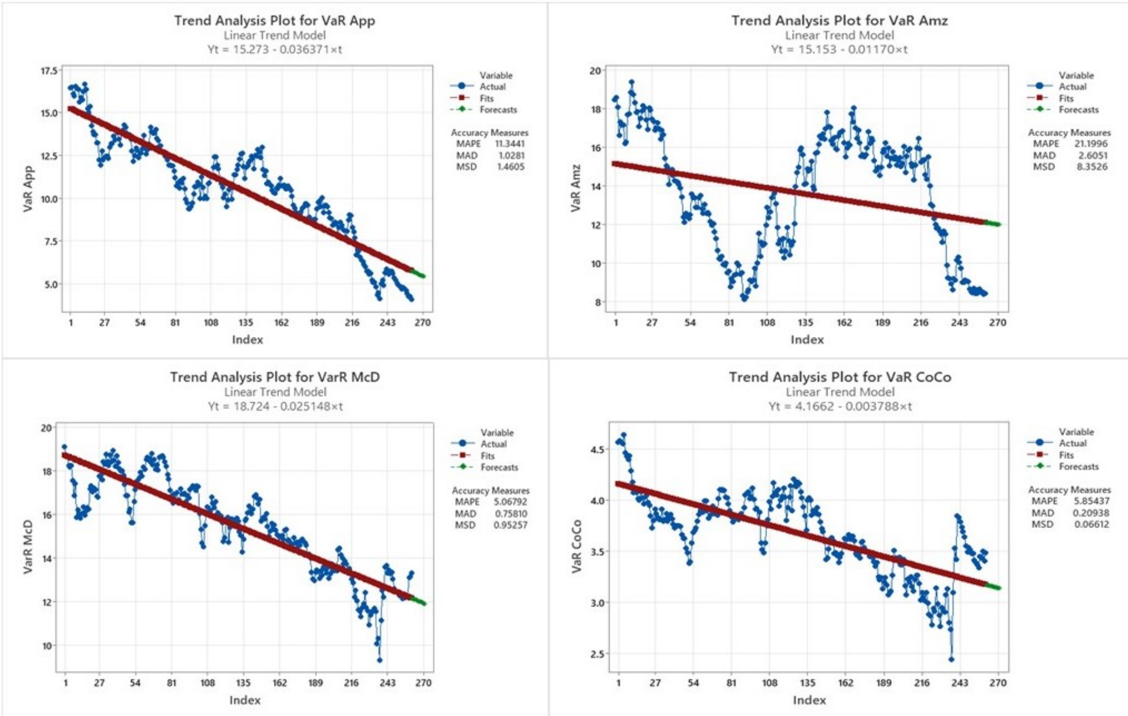

Fig. 2: Main Effects plot for Means

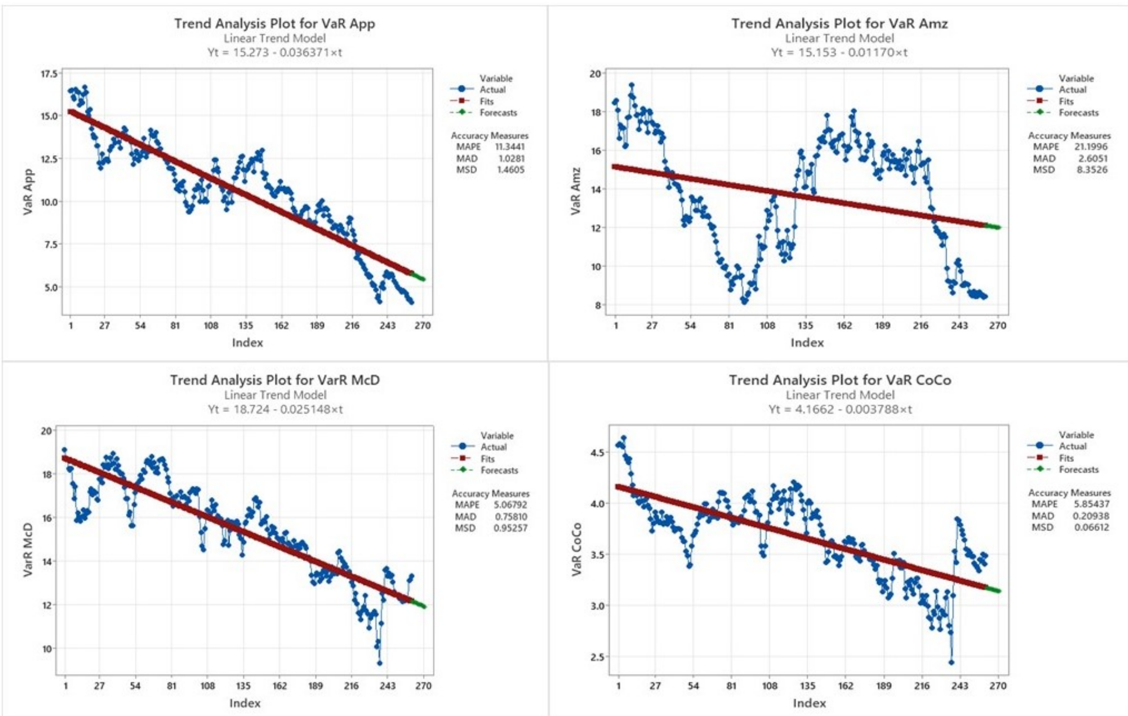

Fig. 3: Normality and stationarity

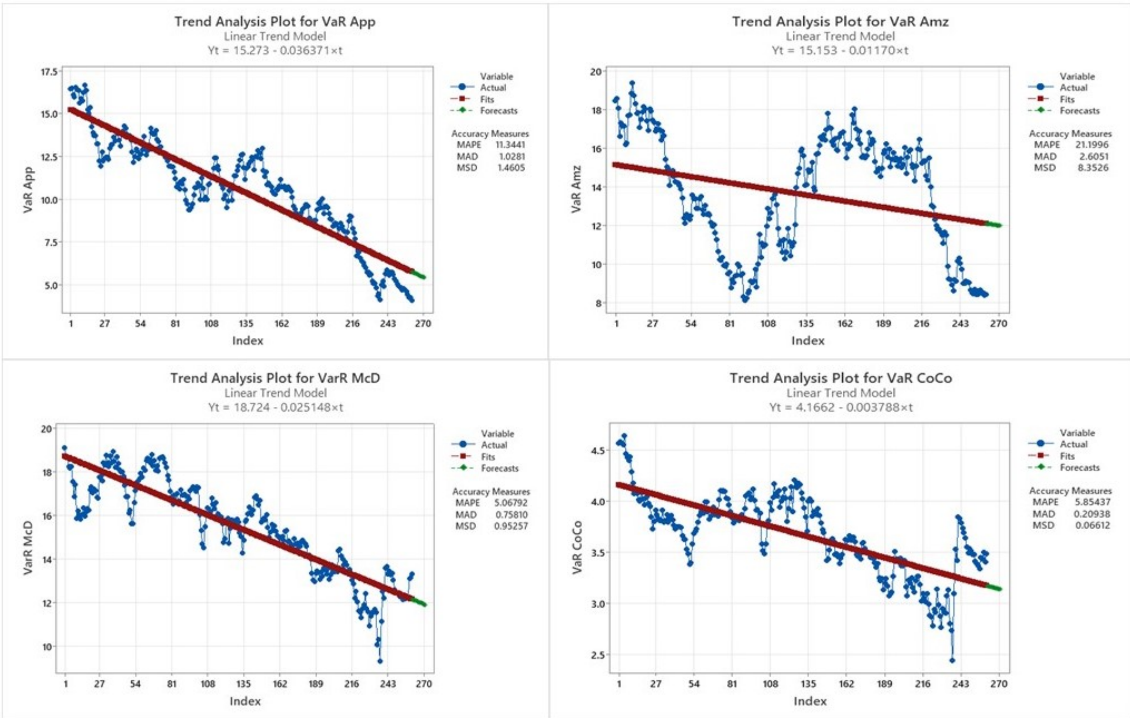

Fig. 4: Trend analysis plots of VaR using the linear trend model for App, Amz, McD, and CoCo. Actual data (blue), fitted trends (red), and forecasted values (green)

Table 7: Forecast

	App	Amz	MCD	CoCo
Period	Forecast	Forecast	Forecast	Forecast
262	5.74364	12.0885	12.1353	3.17381
263	5.70727	12.0768	12.1102	3.17002
264	5.6709	12.0651	12.085	3.16623
265	5.63453	12.0534	12.0599	3.16244
266	5.59816	12.0417	12.0347	3.15866
267	5.56179	12.03	12.0096	3.15487
268	5.52542	12.0183	11.9844	3.15108
269	5.48905	12.0066	11.9593	3.14729
270	5.45268	11.9949	11.9341	3.14351
271	5.4163	11.9832	11.909	3.13972

moderate reductions, with forecasts decreasing from 12.13 to 11.91, while CoCo experiences the smallest changes, with values marginally dropping from 3.17 to 3.14, indicating a stable risk profile. Overall, the forecasts align with observed trends and reflect distinct company-specific risk management strategies.

4.6.1 Accuracy Measure

Accuracy measures—MAPE, MAD, and MSD—are used to evaluate the predictive ability of the linear trend models for the four selected firms. The errors reflect the extent to which forecasted values of VaR are representative of the history data. The lower the value for the error, the higher the performance is, as can be observed from Table 8. The Coca-Cola (CoCo) and McDonald's (McD) model shows good performance, while Amazon (Amz) shows the maximum deviation, which means poor fits. The disparity inaccuracy in prediction can be attributed to various factors. Firstly, a simple linear trend model might not be able to capture the non-linear and intricate nature of financial market dynamics. Secondly, the model is developed on purely internal variables—price, mean return, and standard deviation—with no account for essential external macroeconomic variables such as interest rates, inflation, trading volume, and market volatility indices (such as VIX), which are well-documented factors to move the VaR. Thirdly, company-specific events such as policy changes, earnings announcements, or market dislocations could have introduced irregularities in the data not present in the model. Future research can refine the areas by, for example, incorporating advanced predictive tools such as machine learning models (such as Random Forest, Gradient Boosting, or LSTM networks), which can account for non-linear relationships and can handle high-dimensional data. Secondly, inclusion of

Table 8: Accuracy Measures

	App	Amz	MCD	CoCo
MAPE	11.3441	21.1996	5.06792	5.85437
MAD	1.0281	2.6051	0.75810	0.20938
MSD	1.4605	8.3526	0.95257	0.06612

macroeconomic variables as well as market-level variables would enhance the explainability as well as generalizability of models. Lastly, the application of validation procedures such as cross-validation or rolling origin forecast methods would enhance the robustness for models in testing the predictive ability on different time periods. The refinements would provide reliable and actionable VaR predicting in financial applications for real-life problems.

The conclusion of Table 8 are as follows: MAPE: This measures the average percentage error between actual and predicted values, where lower values indicate better model performance. McD (5.06792) and CoCo (5.85437) have the lowest MAPE, suggesting their models align closely with the data. In contrast, Amz has the highest MAPE (21.1996), indicating a relatively poor model fit. MAD: This represents the average absolute deviation between predicted and actual data, with lower values signifying greater accuracy. CoCo has the smallest MAD (0.20938), followed by McD (0.75810), reflecting precise predictions. App (1.0281) and Amz (2.6051) show higher MAD values, indicating larger deviations.
MSD: This calculates the average squared deviations, giving more weight to larger errors. Lower MSD values represent better fits. CoCo achieves the lowest MSD (0.06612), followed by McD (0.95257), indicating strong model performance. App (1.4605) and Amz (8.3526) have higher MSD values, with Amz being the least accurate. The model for CoCo performs the best overall, with the lowest MAD and MSD and a low MAPE, demonstrating high precision and minimal error. McD also performs well, with slightly higher but still low error measures. Conversely, the models for App and particularly Amz show poorer accuracy, with Amz being the least fit due to significantly higher MAPE, MAD, and MSD values.
Beyond statistical interpretation, the observed trends in VaR also have important business and financial implications. For instance, Apple's steep decline in VaR may reflect heightened volatility and rapid valuation adjustments within the technology sector, which often responds sharply to innovation cycles and market sentiment. In contrast, Coca-Cola's relatively stable risk profile aligns with its position in the consumer staples industry, characterized by steady demand and lower market sensitivity. McDonald's shows moderate risk reduction, indicative of its balanced global exposure and stable cash flows, while Amazon's higher variability may be linked to expansion-driven uncertainty and fluctuating e-commerce dynamics. These interpretations provide practical insights into how industry characteristics and strategic positioning influence firm-level risk behavior.

5 Recommendations and Future Work

The analysis identifies stock price (S_t), standard deviation σ, and mean return (μ) as the most critical variables influencing VaR. Among these, stock price has the greatest impact, indicating that firms should focus on reducing volatility and fostering investor confidence. Effective management of standard deviation through robust risk management practices can help mitigate extreme fluctuations, while optimizing mean returns through portfolio diversification and strategic resource allocation can enhance financial resilience. For companies like Amazon and Apple, improving predictive accuracy may require refining their forecasting models by incorporating additional relevant variables or adopting more advanced analytical techniques.
Future research can involve the inclusion of advanced machine learning algorithms such as Random Forests, Gradient Boosting, or Deep Learning in an effort to identify non-linear relationships better and promote predictive robustness. Such algorithms can also manage high-dimensional data and can even accommodate macroeconomic factors such as interest rates, inflation, market volatility indexes (e.g., VIX), and trading volumes. Moreover, hybrid approaches which include Taguchi design for optimum feature selection and machine learning for predictive modeling can provide powerful, data-based decision-support tools in financial risk assessment.
Assumptions are made for simplicity and for consistency with the Taguchi paradigm that the mean return (μ) and standard deviation of return (σ) remain stable in the study period. We acknowledge that in realistic financial markets, the returns are time-varying and heteroskedastic. Future extensions would be dynamic modeling of volatility (e.g., GARCH or stochastic volatility models) in order to overcome such a simplification.

6 Conclusions

The analysis confirms the effectiveness of the Taguchi L16 method and Simple linear trend model for predicting VaR and assessing parameter impacts across four companies. Stock price S_t is identified as the most influential factor, with a high Sequential SS value of 101.289 and a delta of 6.967, followed by standard deviation σ, while the mean μ has the least impact. Optimal VaR is achieved with maximum $S_t and \sigma$ values and a minimum μ. Trend analysis reveals a consistent decline in VaR over time, with McD having the highest initial VaR, followed by App, Amz, and CoCo. App exhibits the steepest reduction in risk exposure, while CoCo shows a slower, stable decline, reflecting distinct risk management strategies. Performance metrics (MAPE, MAD, MSD) highlight varying model accuracies, with CoCo's model performing best due to its lowest error values, followed by McD. App's model demonstrates moderate accuracy, whereas Amz's model shows the poorest fit, characterized by significantly higher error values.

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The authors declare that they have no competing interest

Availability of data and material

The process parameters and the selected levels are presented in Table1.

Authors' contributions

All authors contributed equally.

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