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Assessing Financial Stability in Turbulent Times: A Study of Generalized Autoregressive Conditional Heteroskedasticity-Type Value-at-Risk Model Performance in Thailand's Transportation Sector during COVID-19

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Abstract: The Value-at-Risk (VaR) metric serves as a pivotal tool for quantifying market risk, offering an estimation of potential investment losses. Predominantly employed within financial sectors, it aids in adhering to regulatory mandates and in devising capital reserve strategies. Nonetheless, the predictive precision of VaR models frequently faces scrutiny, particularly during crises and heightened uncertainty phases. Phenomena like volatility clustering impinge on the accuracy of these models. To mitigate such constraints, conditional volatility models are integrated to augment the robustness and adaptability of VaR approaches. This study critically evaluates the efficacy of GARCH-type VaR models within the transportation sector amidst the Thai stock market's volatility during the COVID-19 pandemic. The dataset encompasses daily price fluctuations in the Transportation Sector index (TRANS), the Service Industry index (SERVICE), and 17 pertinent stocks within the Stock Exchange of Thailand, spanning from 28 December 2018 to 28 December 2023, thereby encapsulating the pandemic era. The employed GARCH-type VaR models include GARCH (1,1) VaR, ARMA (1,1)—GARCH (1,1) VaR, GARCH (1,1)—M VaR, IGARCH (1,1) VaR, EWMA VaR, and csGARCH (1,1) VaR. These are juxtaposed with more traditional, less computationally intensive models like the Historical Simulation VaR and Delta Normal VaR. The backtesting methodologies encompass Kupiec's POF test, the Independence Test, and Christoffersen's Interval Forecast test. Intriguingly, the findings reveal that the Historical Simulation VaR model surpasses GARCH-type VaR models in failure rate accuracy. Within the GARCH-type category, the EWMA VaR model exhibited superior failure rate accuracy. The csGARCH (1,1) VaR and EWMA VaR models emerged as notably robust. These findings bear significant implications for managerial decision-making in financial risk management.

Keywords: VaR Model; risk measures; value at risk; COVID-19; GARCH; transportation; Thailand; backtesting

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Citation: Likitratcharoen, Danai, and Lucksuda Suwannamalik. 2024. Assessing Financial Stability in Turbulent Times: A Study of Generalized Autoregressive Conditional Heteroskedasticity-Type Value-at-Risk Model Performance in Thailand's Transportation Sector during COVID-19. *Risks* 12: 51. https://doi.org/10.3390/risks12030051

Academic Editor: Tak Kuen Ken Siu

Received: 27 January 2024
Revised: 26 February 2024
Accepted: 7 March 2024
Published: 13 March 2024

1. Introduction

Since its inception in 1975, the Stock Exchange of Thailand (SET) has evolved into a formidable global financial hub, significantly contributing to Thailand's economic progress. The SET plays a pivotal role in capital allocation and offers a plethora of investment opportunities to both local and global investors (Sutheebanjard and Premchaiswadi 2010). Recognized as an emerging market, it is often associated with high growth potential (Trakarnsirinont et al. 2023; Meeampol et al. 2014). However, investments in such markets carry inherently higher risks compared with developed markets, as evidenced by their greater volatility and return anomalies (Mody 2003; Bekaert and Harvey 2003; Bekaert et al. 1998).

The COVID-19 pandemic severely impacted the Thai economy, particularly affecting sectors like tourism, hospitality, and transportation. The latter, accounting for a significant portion of Thailand's GDP, faced drastic downturns due to pandemic-induced restrictions

(Chancharat and Meeprom 2022; Ketudat and Jeenanunta 2021). Government-imposed lockdowns precipitated a cascade of economic constraints, disrupting production and mobility (Mazur et al. 2021; Ozili and Arun 2020; Açikgöz and Günay 2020; Sohrabi et al. 2020). This led to a notable decline in the net earnings of the transportation sector, exacerbating operational costs and inefficiencies (Suwannapak and Chancharat 2022; Charoennapharat and Chaopaisarn 2022). The aviation industry, including major airlines such as Thai Airways, faced heightened bankruptcy risks during this period (Maneenop and Kotcharin 2020; Abdullah et al. 2020).

In the realm of market risk management, the Value-at-Risk (VaR) model stands as a critical quantitative tool. It assesses potential financial losses within a given timeframe and confidence interval (Jorion 2011). The complexity of modern financial markets necessitates the need for accurate and reliable VaR models, especially under conditions of market stress and volatility clustering (Sheedy 2008; Mavani 2020). To address these challenges, this paper investigates the effectiveness of conditional volatility models, particularly the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type models. These models, known for their ability to predict market volatility and adapt to rapid risk dynamics, are compared against traditional VaR models such as the Historical Simulation VaR (HS VaR) and Delta Normal VaR (DN VaR). This study specifically focuses on the GARCH (1,1) VaR, ARMA (1,1)—GARCH (1,1) VaR, GARCH (1,1)—M VaR, IGARCH (1,1) VaR, EWMA VaR, and csGARCH (1,1) VaR models. Their accuracy and robustness are evaluated in the context of the transportation sector's stock performance during the COVID-19 crisis.

Given the crucial role of the Stock Exchange of Thailand (SET) in the nation's economic landscape and its emergence as a significant player in the global financial market, this study aims to address several pertinent questions within the realm of market risk management during the tumultuous period of the COVID-19 pandemic. Firstly, amidst the inherent risks and volatilities associated with emerging markets such as Thailand, how do various Value-at-Risk (VaR) models, particularly the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type models, perform in predicting financial risks in the transportation sector, which is a critical component of Thailand's GDP? Secondly, in comparing these GARCH-type VaR models against traditional models such as Historical Simulation VaR and Delta Normal VaR, what insights can be gleaned regarding their relative efficacy and robustness in the face of unprecedented market stress and volatility? This investigation is not only academically significant but also essential for practitioners in financial risk management, offering a nuanced understanding of model performance during an extraordinary economic disruption.

2. Literature Review

2.1. Value-at-Risk Concepts and Limitations

Value-at-Risk (VaR) is conceptualized as the maximum projected loss over a defined investment horizon at a specified confidence interval (Jorion 2011; Holton 2002). It is a cornerstone in the financial industry, primarily utilized for assessing the adequacy of capital reserves (Jiménez-Martín et al. 2009; Taskinsoy 2022). The mathematical representation of VaR is articulated as:

$$\mathrm{VaR}_{\alpha}(\mathrm{X}) = -\inf\{x \in \mathbb{R} : \mathrm{F}_{x}(x) > \alpha\} \tag{1}$$

where X is a distribution of profit and loss of investment and α is the confidence level at which the possibility of a loss is measured.

The applicability of VaR transcends various asset classes. In the realm of high-risk assets like cryptocurrencies, research indicates a superior performance of non-parametric approaches over those predicated on normality assumptions (Likitratcharoen et al. 2018, 2021, 2023). In emerging markets, the deployment of Extreme Value Theory (EVT) for VaR forecasting has garnered attention. Gençay and Selçuk (2004) advocated for the use of EVT-based VaR at higher quantiles in such markets. Cifter (2011) underscored the enhanced predictive precision of VaR models via wavelet-based EVT. Bao et al. (2006) discerned that EVT VaR models exhibit superior accuracy during financial turmoil, while EWMA

VaR models are more effective in stable periods. Seymour and Polakow (2003) posited that the amalgamation of rolling GARCH forecasts with EVT principles yields augmented outcomes in the South African stock market. De Jesús and Ortiz (2011) demonstrated that EVT-based Conditional Value at Risk (CVaR) effectively captures the return distribution in emerging markets, characterized by their pronounced kurtosis and leptokurtic nature. Nonetheless, Dimitrakopoulos et al. (2010) observed that most VaR models, irrespective of their assumptions regarding fat tails, tend to overestimate risk in emerging markets.

The robustness of VaR models during financial crises has been a subject of intense scrutiny. Mavani (2020) concluded that traditional VaR methodologies including HS VaR, DN VaR, and Monte Carlo Simulation VaR models were inadequate during financial crises. Kourouma et al. (2010) found that VaR, particularly the HS VaR approach, consistently underestimated risks during the 2008 financial crisis. A similar vein of findings by Skoglund et al. (2010) also highlighted the underestimation of risk by traditional VaR but suggested that GARCH and copula methodologies could enhance VaR's precision. Degiannakis et al. (2012) posited that GARCH frameworks not only ameliorate VaR accuracy during financial crises but also in phases of heightened volatility. Hajihasani et al. (2021) demonstrated the superior performance of q-Gaussian distribution VaR models over traditional normality-based VaR models. In line with this, Abad et al. (2016) found that skewed distribution models outperform both normal and Student T distributions during financial distress. Miletic and Miletic (2015) further corroborated the superiority of GARCH-type VaR models over traditional variants. Traditional VaR models' inability to account for volatility clustering was highlighted by Sheedy (2008), while Yalmaz and Byström (2014) argued that models with extensive observation windows lack the agility to adapt to abrupt volatility shifts, rendering the EWMA VaR model as less accurate. Within the context of the Stock Exchange of Thailand, the efficacy of VaR models has been sporadically explored. Sethapramote et al. (2014) discovered that the long-memory FIGARCH VaR model surpassed the standard GARCH model in the SET50 index. Jongadsayakul (2021) indicated a superior performance of historical simulation and asymmetric GARCH-type VaR models compared with parametric and semi-parametric VaR models. This comprehensive review underscores the multifaceted nature of VaR methodologies and their varied effectiveness across different financial contexts, particularly in emerging markets and during periods of economic instability.

2.2. COVID-19 Pandemic and the Transportation Sector

The onset of the COVID-19 pandemic, initially a localized health crisis in China, swiftly transformed into a global catastrophe, exerting profound ramifications on the international economy. This pandemic precipitated a deceleration in production and economic activities, adversely affecting various sectors worldwide (Mazur et al. 2021; Ozili and Arun 2020; Açikgöz and Günay 2020; Sohrabi et al. 2020). The stock markets globally exhibited marked negative responses, reflecting investor apprehensions regarding the economic implications of the pandemic (Ramelli and Wagner 2020; Baker et al. 2020). Specifically, the Thai stock market demonstrated unfavorably asymmetric volatility, with stock returns inversely correlated with the escalation in COVID-19 cases within Thailand (Suwannapak and Chancharat 2022).

The transportation sector, a crucial component of the global supply chain, was significantly impacted by the pandemic. The abrupt decline in international tourism, particularly in Thailand where tourist numbers plummeted by 83%, inflicted severe financial strain on related industries, including transportation. Prominent airlines, such as Thai Airways and Bangkok Airways, encountered substantial economic challenges (Maneenop and Kotcharin 2020; Abdullah et al. 2020). Empirical analysis by Abdullah et al. (2020) highlighted an increased bankruptcy risk for Thai Airways as a direct consequence of the pandemic. Concurrently, the cargo shipping segment experienced volatile market responses, evidenced by abnormal returns in stock values, further compounded by container supply shortages (Marobhe 2022). Research by Charoennapharat and Chaopaisarn (2022) identified escalated transportation costs, elongated delivery times, and increased insurance expenditures as primary challenges during this period. Additionally, lockdown measures and altered transportation practices led to operational inefficiencies within transportation companies, as elucidated by Aunyawong et al. (2021). As a cumulative effect of these disruptions, the transportation sector witnessed a pronounced decline in net earnings, the most significant across all sectors (Suwannapak and Chancharat 2022). This narrative underscores the extensive impact of the COVID-19 pandemic on the transportation sector, highlighting the resultant financial difficulties and operational challenges.

3. Data Acquisition and Methodological Framework

This study utilizes an extensive dataset comprising daily price indices of the transportation sector (TRANS) and the service industry (SERVICE) from the Stock Exchange of Thailand, in addition to daily prices of 17 equity stocks within the transportation sector. These data, meticulously sourced from the SETSMART database, span from 28 December 2018 to 28 December 2023. This period encapsulates the turbulent phase of the Thai stock market during the COVID-19 pandemic, characterized by pronounced uncertainty and market volatility.

The dataset's daily returns are computed employing the logarithmic return method, succinctly represented by the equation:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{2}$$

where r_t denotes the return at time t, P_t is the price at time t, and $P_{(t-1)}$ is the price at time $t-1$.

In this research, the focus is squarely on the daily returns of each individual investment. These returns are pivotal in the computation of the Value-at-Risk (VaR) for each investment, in accordance with the distinct characteristics and methodologies inherent to each VaR model. The empirical accuracy of each VaR model is subjected to rigorous backtesting, employing a trio of methodological tests including the unconditional coverage test, the independence properties test, and the conditional coverage test. The ensuing section delineates in-depth insights into each model's specificities and the employed backtesting methodologies, thereby providing a comprehensive overview of this study's analytical framework.

3.1. Value-at-Risk Models: GARCH-VaR Methodologies

In the ambit of this study, the focus is directed towards the application of Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-based Value-at-Risk (VaR) models for the prognostication of downside investment risks. Within these models, the distribution of the error terms and the asset returns are posited to conform to a normal distribution framework. The mathematical formulation of the GARCH-VaR model is delineated as:

$$\mathrm{VaR}_{t|t-1} = \mu + Z_\alpha \hat{\sigma}_{t|t-1} \tag{3}$$

Each component of the equation is explained as follows:

$\mathrm{VaR}_{t|t-1}$: This represents the Value-at-Risk at time t, forecasted using data available up until time $t-1$. It is a measure of the maximum expected loss over a specified time frame, calculated at a particular confidence level.

μ: This symbol typically denotes the mean or expected value of the returns of the financial asset or portfolio over the specified time period. It represents the average or typical value around which the returns are expected to fluctuate.

Z_α: This is the Z-score corresponding to the desired confidence level α. The Z-score is a statistical measure that describes a value's relationship to the mean of a group of values, expressed in terms of standard deviations. For instance, for a 95% confidence level, Z_α; would be the Z-score that corresponds to the 95th percentile of the standard normal distribution.

$\hat{\sigma}_{t|t-1}$: This denotes the estimated standard deviation (volatility) of the asset's or portfolio's returns at time t, based on the information available up to time $t - 1$. The standard deviation is a common measure of the variability or dispersion in a set of values.

This research employs a rolling forecast methodology to dynamically incorporate new data, thereby enhancing the model's responsiveness to recent market developments. The rolling data window for each day's estimation (tt) extends from the preceding day (t−1t−1) to 250 trading days prior (t−250t−250). The frequency of GARCH parameter re-estimation is strategically set at a 20-day interval. This approach is informed by the findings of Angelidis et al. (2004), who advocate for the utilization of the most recent data to augment the precision of GARCH parameter estimates. Contrastingly, the research of Su (2015) suggests that the addition of new data does not invariably enhance model accuracy. Further, the investigation by Ardia and Hoogerheide (2014) reveals that the frequency of parameter updates—whether daily, weekly, monthly, or quarterly—imparts only minimal impact on the accuracy of GARCH models. Thus, the chosen re-estimation frequency in this study seeks to strike a balance between computational efficiency and the maintenance of an acceptable level of accuracy in GARCH parameter estimations.

3.2. GARCH (1,1) VaR Model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model is esteemed in the quantitative finance field as a potent statistical mechanism for prognosticating the volatility inherent in financial asset returns. This model is predicated on the principle that significant historical market shocks precipitate enhanced variances in the subsequent period, thus effectively encapsulating the characteristic phenomenon of volatility clustering frequently observed in financial markets.

Formally, the GARCH (1,1) model is expressed as the equation:

$$\hat{\sigma}_t^2 = \omega + \alpha y_{t-1}^2 + \beta \hat{\sigma}_{t-1}^2 \tag{4}$$

Within the above equation, the term σ_t^2 denotes the forecasted conditional variance for time t, and y_t symbolizes the residual or unexpected return on day t. The residual y_t is theorized to equate to $\sigma_t \epsilon_t$, wherein ϵ_t adheres to an independent and identically distributed standard normal distribution ($\epsilon_t \sim \text{iid.}(0,1)$). The coefficients ω, α, and β require careful estimation through historical return data analysis. It is of paramount importance for the validity and precision of the model that these parameters are maintained within positive realms, ensuring the model's robustness and accuracy in forecasting outcomes (Dimopoulou 2017).

3.3. ARMA (1,1)—GARCH (1,1) VaR: An Integrated Approach for Forecasting Returns and Volatility

The ARMA (1,1)-GARCH (1,1) model represents a sophisticated amalgamation of the Autoregressive Moving Average (ARMA) model for predicting returns and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model for forecasting conditional volatility. The ARMA component elucidates the dynamics of lagged returns, primarily utilized to model the mean of returns. The Autoregressive (AR) element of the model utilizes historical values within the time series to forecast returns. Simultaneously, the Moving Average (MA) segment enhances the model's adaptability by rectifying the forecast of current values based on previous forecasting errors (Tsay 2005; Ghani and Rahim 2019). The ARMA (1,1) model can be mathematically represented as:

$$r_t = c + \phi r_{t-1} + \theta y_{t-1} + y_t \tag{5}$$

and reformulated as:

$$y_t = r_t - c - \phi r_{t-1} - \theta y_{t-1} \tag{6}$$

where c, ϕ, and θ are the model parameters that necessitate estimation.

3.4. GARCH (1,1)—M: Integrating Volatility in Mean Equations

The GARCH (1,1)-M or GARCH-in-Mean model extends the conventional GARCH model by embedding the volatility component within the mean equation. This model acknowledges that expected asset returns may be influenced by volatility, thus integrating volatility as a potential determinant of security returns (Xi 2018). The GARCH (1,1)-M model can be succinctly expressed as:

$$r_t = c + \lambda\hat{\sigma}_t + y_t \tag{7}$$

or reformulated as:

$$y_t = r_t - c - \lambda\hat{\sigma}_t \tag{8}$$

In the above formulation, rt signifies the return on day t, σ_t represents the predicted volatility at time t, and y_t denotes the residual component. The parameter c, also referred to as the risk premium parameter, elucidates the interrelationship between return and volatility. A positive value of c indicates a direct correlation between these two variables, suggesting that higher volatility is associated with higher expected returns (Tsay 2005).

3.5. IGARCH (1,1) VaR: Refinement of Standard GARCH through the Unit-Root Constraint

The Integrated Generalized Autoregressive Conditional Heteroskedasticity (IGARCH) (1,1) Value-at-Risk model is a variant of the canonical GARCH model, distinguished by the incorporation of a unit-root constraint. This constraint enforces a specific relationship among the model's parameters, notably, the sum of the coefficients α and β equating to unity (Gabriel 2012). In this framework, the α coefficient in the IGARCH (1,1) model is recalibrated by substituting it with the value of 1 minus β, thereby adhering to the constraint:

$$\hat{\sigma}_t^2 = \omega + (1-\beta)y_{t-1}^2 + \beta\hat{\sigma}_{t-1}^2 \tag{9}$$

3.6. EWMA VaR: Assigning Differential Weights to Historical Observations

The Exponentially Weighted Moving Average (EWMA) Value-at-Risk model differentiates itself by allocating varied weights to historical data points, with an increased focus on recent market movements. This attribute enables the model to rapidly respond to market downturns and significant fluctuations (Korkmaz and Aydın 2002; Armanda et al. 2022). JPMorgan's Riskmetrics suggests values like 0.94 for daily estimates and 0.97 for monthly estimates. The model's equation is articulated as:

$$\hat{\sigma}_t^2 = (1-\lambda)y_{t-1}^2 + \lambda\hat{\sigma}_{t-1}^2 \tag{10}$$

This formulation aligns closely with the structure of the IGARCH model (Manganelli and Engle 2001).

3.7. csGARCH (1,1) VaR: Unveiling Long-Term and Short-Term Volatility Impacts

The Component Standard GARCH (csGARCH) (1,1) model augments the volatility estimation capabilities of the traditional GARCH model by dissecting and analyzing the effects of both short-term and long-term volatility shocks. By distinguishing these volatility components, the csGARCH model offers a nuanced analysis of persistent and ephemeral market changes. Its ability to capture the complex interplay and fluctuations in financial data significantly enhances our understanding of the underlying forces driving financial markets (Wang et al. 2022; Chu et al. 2017; Engle and Lee 1999). The csGARCH model is mathematically formulated as:

$$\hat{\sigma}_t^2 = q_t + \alpha(y_{t-1}^2 - q_{t-1}) + \beta(\hat{\sigma}_{t-1}^2 - q_{t-1}) \tag{11}$$

$$q_t = \omega + \rho q_{t-1} + \phi(y_{t-1}^2 - \hat{\sigma}_{t-1}^2) \tag{12}$$

where q_t symbolizes the long-term or permanent component of volatility, while $\sigma^2_{t-1} - q_{t-1}$ reflects the influence of short-term volatility shocks.

3.8. HS VaR: A Non-Parametric Approach to Quantile Estimation

The Historical Simulation (HS) Value-at-Risk (VaR) model distinguishes itself from its parametric counterparts by eschewing assumptions regarding the distributional shape and parameters of financial returns. This model derives the quantile of historical returns, thereby offering flexibility to accommodate a variety of distributional shapes. However, it is not devoid of assumptions. The HS VaR model presupposes that future investment returns will mirror the historical returns dataset, a premise that underlies its quantile estimation (Likitratcharoen et al. 2021, 2023; Pritsker 2006). The model's equation is formulated as:

$$\mathrm{VaR}_{t+1} = Q_\alpha \{r_t\}_{t=1}^{n} \tag{13}$$

where Q_α represents the α-quantile of the returns data.

3.9. DN VaR: A Parametric Model Based on Normal Distribution Assumptions

The Delta Normal (DN) VaR model is predicated on the assumption of normal distribution parameters for financial returns, thereby streamlining the computation process. This simplification, while advantageous in terms of computational efficiency, may not accurately reflect the actual distribution of returns in scenarios characterized by complex market dynamics and non-linear market conditions (Linsmeier and Pearson 2000). The DN VaR model is expressed through the equation:

$$\mathrm{VaR}_t = \mu + Z_\alpha \sigma \tag{14}$$

where μ denotes the expected return of an investment, calculated as the average value of the returns data, while σ represents the constant volatility or standard deviation of the returns. This model's reliance on normal distribution parameters positions it as a more straightforward, yet potentially less nuanced, approach compared with models that account for more complex distributional characteristics.

3.10. Backtesting Methodologies

In the realm of financial model validation, backtesting methodologies play a crucial role in assessing the reliability and accuracy of predictive models. Zhang and Nadarajah (2018) systematically categorized backtesting methods into four primary types as follows: unconditional coverage tests, conditional coverage tests, independence property tests, and other varied approaches. This paper employs a triad of backtesting methodologies including Kupiec's Proportion of Failures (POF) test, the Independence Test as formulated by Christoffersen (1998), and Christoffersen's Interval Forecast test. Each of these methodologies is expounded upon in detail below.

3.11. Kupiec's POF Test: Evaluating VaR Model Accuracy

Kupiec's POF test serves as a critical tool in VaR backtesting. It assesses model accuracy by juxtaposing expected losses against actual losses using historical data. This test scrutinizes whether the VaR model's violations are congruent with the anticipated levels, particularly focusing on instances where actual losses exceed the VaR estimates. Discrepancies in this alignment may indicate potential inaccuracies within the VaR model. An overestimation of risk leads to a notably lower failure rate, whereas an underestimation results in a higher failure rate (Halilbegovic et al. 2019; Campbell 2005). The null hypothesis for this test is:

$$H_0 : p = \hat{p} \tag{15}$$

The test statistic is derived from a likelihood function following a Chi-squared distribution with one degree of freedom:

$$LR_{POF} = -2\ln\left(\frac{(1-p)^{n-x}p^x}{\left(1-\left(\frac{x}{n}\right)\right)^{n-x}\left(\frac{x}{n}\right)^x}\right) \sim \chi^2(1) \tag{16}$$

where n represents the total number of observations and x denotes the actual number of observations where violations occurred.

3.12. Independence Test: Assessing Violation Dependencies

The Independence Test, conceptualized by Christoffersen (1998), evaluates the model's robustness by investigating the dependencies of violation probabilities. It postulates that the likelihood of a violation on a given day should not be contingent upon the outcome of the previous day (Halilbegovic et al. 2019). The null hypothesis is articulated as:

$$H_0 : \pi_0 = \pi_1 \tag{17}$$

where π_0 and π_1 represent the probabilities of a violation occurring on a day following a non-violated and violated day, respectively. The likelihood statistic is formulated as:

$$LR_M = -2\ln\left(\frac{(1-\pi)^{n_{00}+n_{01}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0{}^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1{}^{n_{11}}}\right) \sim \chi^2(1) \tag{18}$$

where

$$\pi_0 = \frac{n_{01}}{n_{00}+n_{01}},\ \pi_1 = \frac{n_{11}}{n_{10}+n_{11}},\ \text{and } \pi = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}} \tag{19}$$

3.13. Christoffersen's Interval Forecast Test: A Combined Approach

The Christoffersen's Interval Forecast test, also known as the Joint test, is a conditional methodology that amalgamates the principles of Kupiec's POF test and the Independence Test. This test extends beyond the scope of unconditional coverage tests by also considering the sequential patterns in violations (Kaszyński et al. 2020; Haas 2001). The likelihood statistic for this test is expressed as:

$$LR_{CC} = LR_{POF} + LR_M \sim \chi^2(2) \tag{20}$$

This comprehensive approach offers a robust mechanism for evaluating the predictive accuracy and reliability of VaR models, especially in the context of dynamic and complex financial markets.

Table 1 encapsulates a comprehensive overview of the VaR models employed in this empirical investigation. This table methodically delineates each model, offering succinct yet informative descriptions and highlighting their distinct features. The models encompass a range of methodologies, from the GARCH (1,1) VaR, which adeptly captures volatility clustering and mean reversion, to the csGARCH (1,1) VaR, renowned for addressing skewness in financial data. Each entry in the table is meticulously curated to provide the reader with an understanding of the model's theoretical underpinnings and practical applications, particularly in the context of financial risk assessment during the volatility witnessed in the COVID-19 era. This tabular representation serves as a pivotal reference point within the Methodology Section, facilitating a nuanced comprehension of the complex quantitative tools used in this study.

Table 1. Summary of GARCH-type Value-at-Risk (VaR) models used in this study.

Model Name	Description	Features
GARCH (1,1) VaR	A model that captures volatility clustering and mean reversion common in financial time series.	Adjusts to rapid changes in market conditions and provides dynamic risk estimates.
ARMA (1,1)—GARCH (1,1) VaR	Combines the ARMA model for capturing autocorrelations in time series data with the GARCH model for volatility modeling.	Useful for series with both autocorrelation and volatility clustering.
GARCH (1,1)—M VaR	Incorporates a risk premium that is proportional to the conditional variance in the asset returns.	Accounts for the time-varying risk premium in financial markets.
IGARCH (1,1) VaR	A variant of the GARCH model where the sum of the alpha and beta coefficients is set to one, implying a persistent shock to volatility.	Useful for modeling long-term impacts of shocks on volatility.
EWMA VaR	Exponentially Weighted Moving Average model giving more weight to recent observations for volatility calculation.	Emphasizes recent market conditions and reacts quickly to market changes.
csGARCH (1,1) VaR	Conditional Skewness GARCH model capturing both volatility and skewness in data.	Addresses asymmetry in data, which is often observed in financial returns.

4. Results

Figure 1 offers a sophisticated analytical depiction, illustrating the daily returns of the Transportation Sector index (TRANS) alongside Value-at-Risk (VaR) trajectories at divergent confidence intervals. The manifestation of VaR breaches is effectively visualized and observable when the daily returns, denoted by blue dots, descend beneath the VaR threshold line. This graphic elucidation provides a clear indication of the escalated volatility experienced in the Thai stock market during the COVID-19 pandemic, a period marked notably by the activation of circuit breaker mechanisms in 2020.

A critical aspect of Figure 1 is its illustration of the adaptability of various VaR models in response to the sudden and significant shifts in risk levels characteristic of this tumultuous period. Notably, the GARCH-type VaR models are portrayed as exhibiting a more rapid and effective adaptation to these abrupt market dynamics when compared with the Historical Simulation (HS) VaR and Delta Normal (DN) VaR models. This visual representation not only underscores the heightened market volatility during the pandemic but also serves as an empirical testament to the comparative efficacy and responsiveness of different VaR models in adjusting to rapidly changing risk environments.

Figure 2 is an academically styled representation, featuring a box plot that aggregates the actual failure rates of a range of Value-at-Risk (VaR) models as applied to the daily returns of 17 transportation sector stocks traded on the Stock Exchange of Thailand. Additionally, the plot encompasses data from the Transportation Sector index (TRANS) and Service Industry index (SERVICE). This visual presentation aids in the comparative analysis of the performance of these VaR models under varying market conditions.

In this figure, dashed lines are strategically placed to denote the theoretical failure rates associated with each specified confidence level of VaR. These include a 1% failure rate for a 99% confidence level VaR, a 5% failure rate for a 95% confidence level VaR, and a 10% failure rate for a 90% confidence level VaR. These benchmarks are critical for evaluating the performance of the VaR models against expected standards.

The calculated failure rates, as illustrated in Figure 2, are subject to empirical validation through the application of Kupiec's Proportion of Failures (POF) test. This test is instrumental in ascertaining the accuracy of the VaR models in predicting risk levels, thereby providing a robust measure of their reliability and effectiveness in real-world market scenarios. The juxtaposition of actual failure rates against theoretical benchmarks in this box plot offers a comprehensive perspective on the efficacy of various VaR models in the context of the Thai transportation sector.

Figure 3 elucidates the p-values derived from Kupiec's Proportion of Failures (POF) test, a critical tool in the evaluation of Value-at-Risk (VaR) models. Within this figure, dashed lines demarcate the alpha level of the test, set at 0.05, against which the performance of the VaR models is scrutinized. This statistical threshold is pivotal in determining the validity of the models' risk predictions.

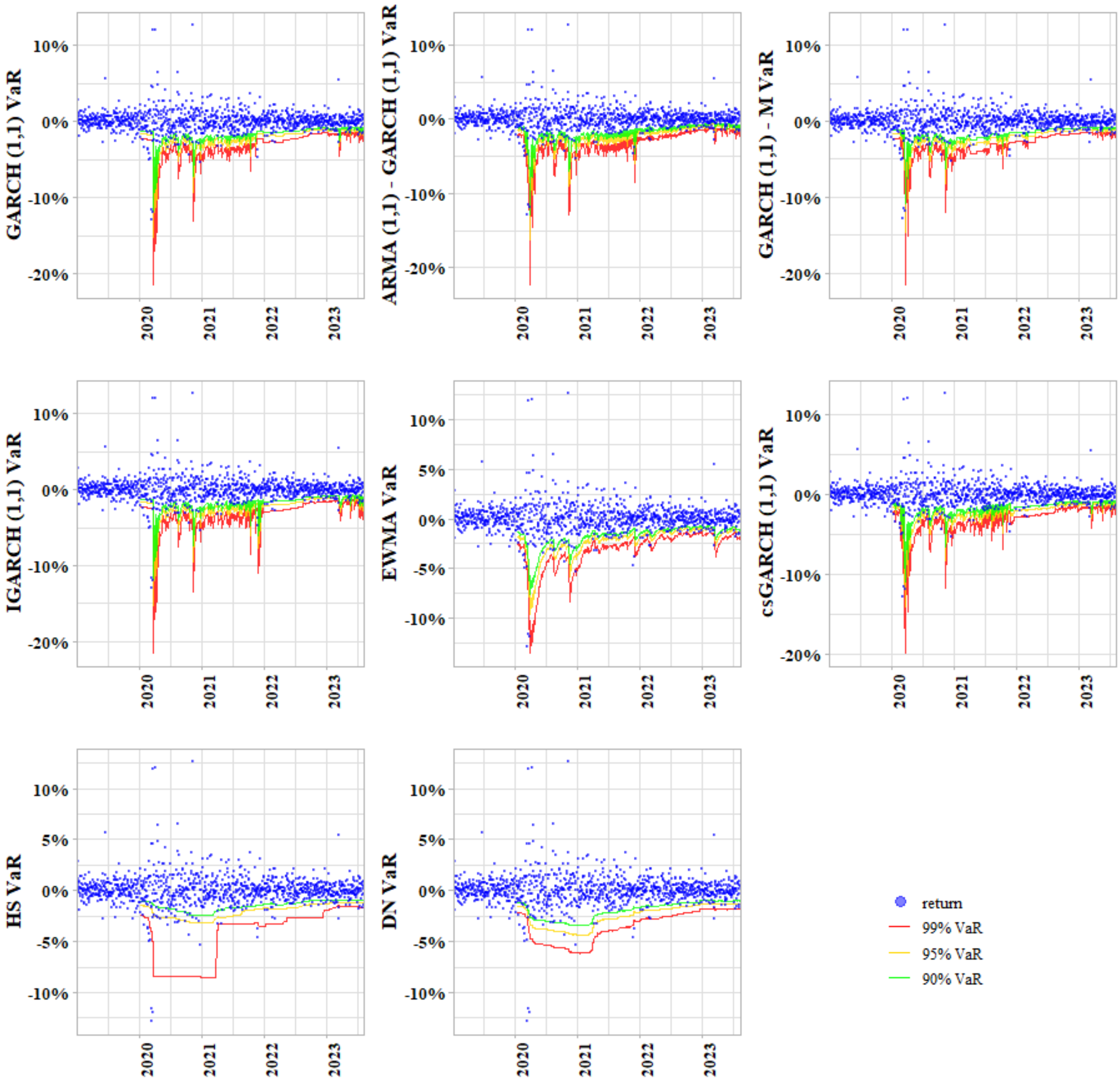

Figure 1. Example of daily returns and VaR plots.

An analytical examination of the failure rates plot and the corresponding test outcomes enables several inferences. At the 99% confidence level, it is evident that the VaR models generally tend to underestimate risks. This is manifested in failure rates exceeding the expected 1%, thus indicating a significant deviation from the anticipated risk threshold. Conversely, at the 90% confidence level, the GARCH-type VaR models, along with the Delta Normal (DN) VaR model, exhibit a tendency to overestimate risks. This is evidenced by markedly lower realized failure rates, suggesting a conservative approach to risk estimation. In this context, the Historical Simulation (HS) VaR model demonstrates a relatively accurate prediction of failure rates, though it occasionally underestimates risk.

Optimal performance among GARCH-type VaR models is observed at the 95% confidence level. Notably, models that incorporate mean equations, such as the ARMA(1,1)—GARCH(1,1) VaR and the GARCH (1,1)—M VaR, exhibit superior performance. However, these models are not immune to risk overestimation, as reflected in both the failure rates and the test results. DN VaR models predominantly show a proclivity for the overestimation of risks at this confidence level.

In an overall assessment, the nonparametric HS VaR method stands out for its accuracy in estimating failure rates, surpassing its parametric counterparts. A particularly intriguing finding is the performance of the Exponentially Weighted Moving Average (EWMA) VaR model. Despite being a less computationally demanding variant within the GARCH model spectrum, it demonstrates the most accurate failure rates among all the GARCH-type VaR models assessed. This revelation underscores the potential of simpler, yet effective, models in accurately predicting market risks under varied conditions.

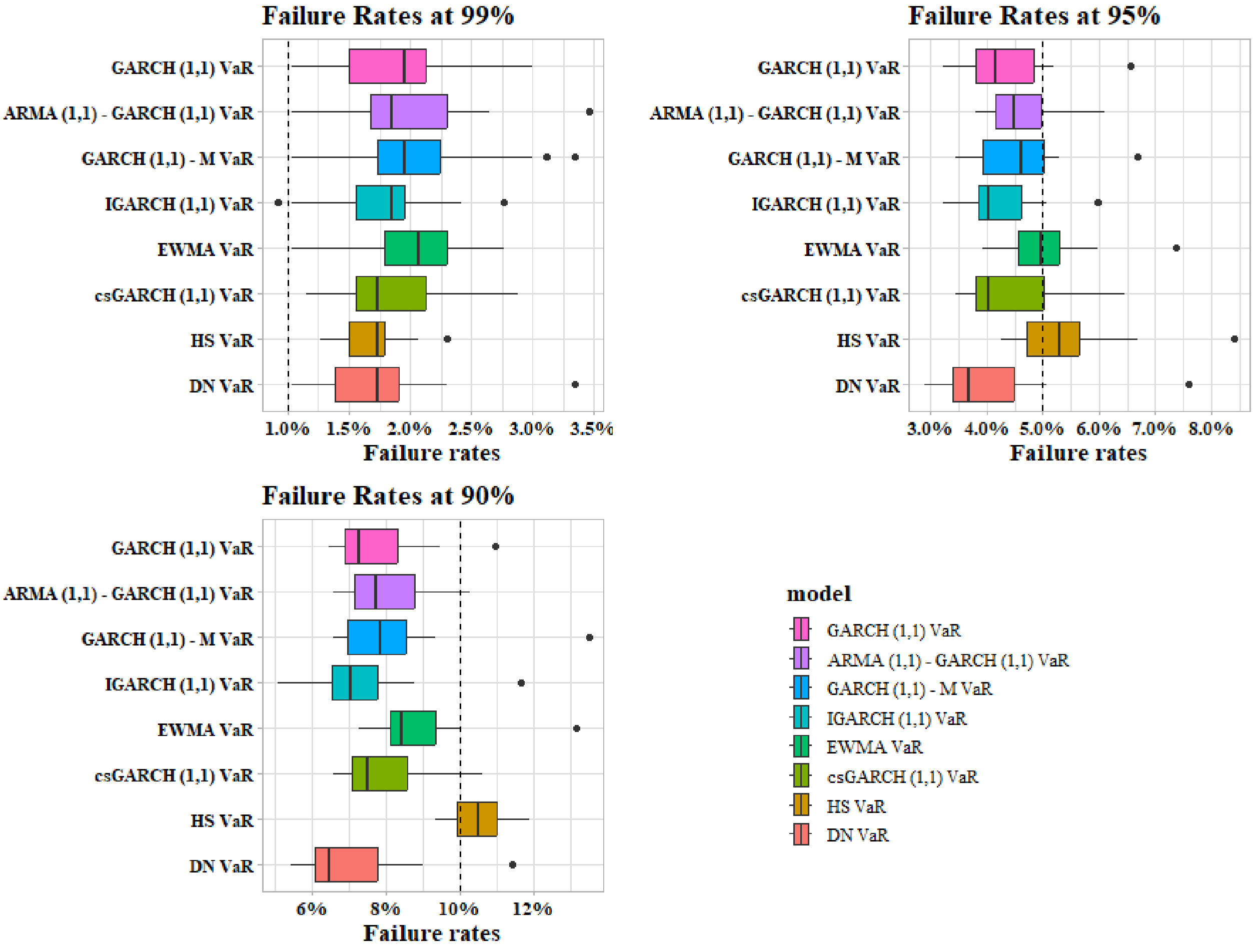

Figure 2. Realized failure rates of each model.

The *p*-values obtained from the Independence Test, as depicted in Figure 4, indicate a relative parity in robustness across the evaluated models. Despite the application of conditional volatility estimations in the computation of Value-at-Risk (VaR), there is discernible evidence suggesting the presence of dependencies in the probabilities of violations. Such dependencies may be ascribed to the anomalous market conditions engendered by the COVID-19 pandemic, which precipitated a significant market downturn.

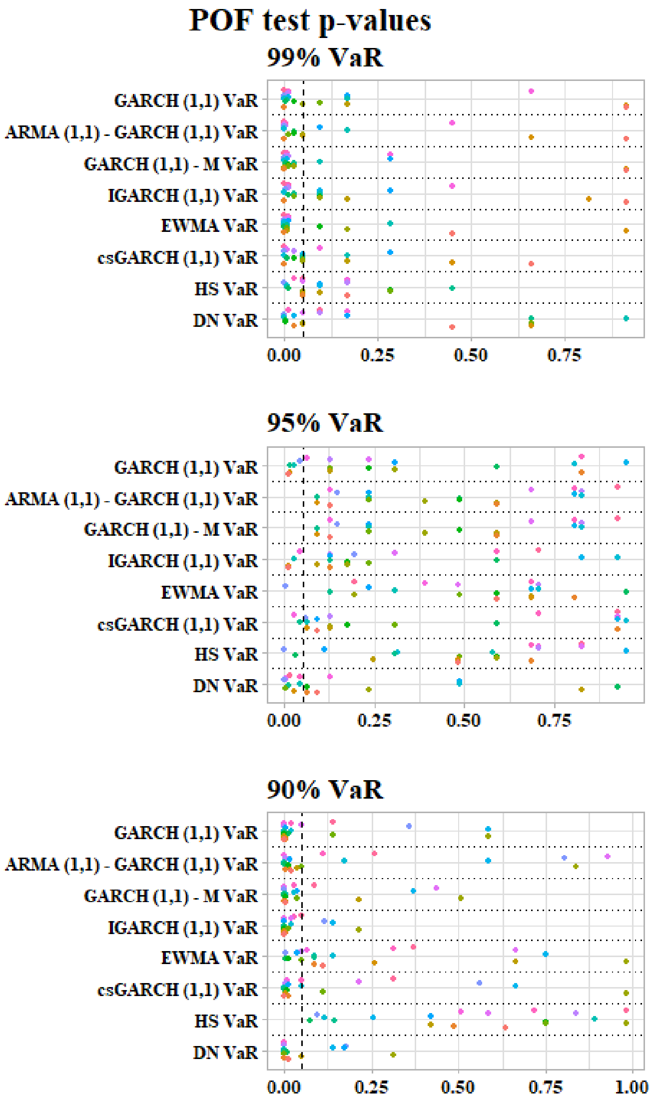

Figure 3. Kupiec's POF test p-value. The varying colors of dots are used to symbolize different transportation companies.

Furthermore, the empirical results elucidate that the csGARCH (1,1) VaR and Exponentially Weighted Moving Average (EWMA) VaR models marginally surpass their counterparts in terms of robustness, particularly at the 90% confidence threshold. This enhanced robustness is indicative of superior performance in capturing and adjusting to the market dynamics during the pandemic.

Notwithstanding the aforementioned, the VaR models exhibited a diminution in robustness when applied to stocks characterized by elevated risk profiles. This observation may highlight a potential limitation in the models' capacity to accurately predict risk for highly volatile stocks, underscoring the necessity for further refinement of these risk assessment tools, especially in the context of markets subjected to extreme and rapid changes.

Figure 5 presents the p-values obtained from Christoffersen's Interval Forecast test, providing an empirical evaluation of the performance of various VaR models at distinct confidence intervals. The results, as illustrated, indicate that the models achieve an optimal performance benchmark at the 95% confidence level. This suggests a commendable level of predictive accuracy within this probability threshold.

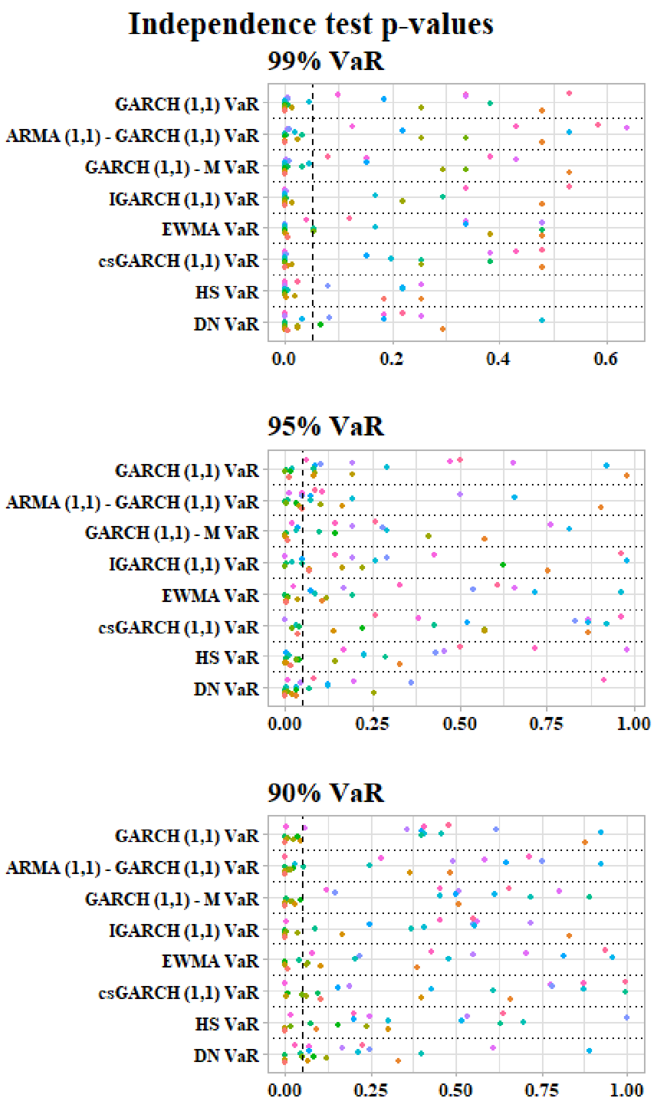

Figure 4. Independence Test *p*-values. The varying colors of dots are used to symbolize different transportation companies.

Table 2, as presented, is a structured synthesis of the VaR backtesting methodologies applied within this study, aligning them with respective confidence levels and corresponding figure references. This table categorizes the backtesting approaches, namely, Realized Failure Rates, Kupiec's Proportion of Failures (POF) test *p*-values, Independence Test *p*-values, and Christoffersen's Interval Forecast test *p*-values. Each backtesting method is considered at confidence levels of 90%, 95%, and 99%, reflecting the range of standard thresholds for risk management within financial sectors.

Table 2. Centralizing table of defining parameters for VaR models.

VaR BackTesting Model	Confidence Level	VaR Model	Figure Reference
Realized Failure Rates	90, 95, 99	GARCH(1,1)	Figure 2
Kupiec's POF test *p*-values	90, 95, 99	ARMA(1,1)	Figure 3
Independence Test *p*-values	90, 95, 99	IGARCH(1,1)	Figure 4
Christoffersen's Interval Forecast test *p*-values	90, 95, 99	EWMA csGARCH(1,1), HS, DN	Figure 5

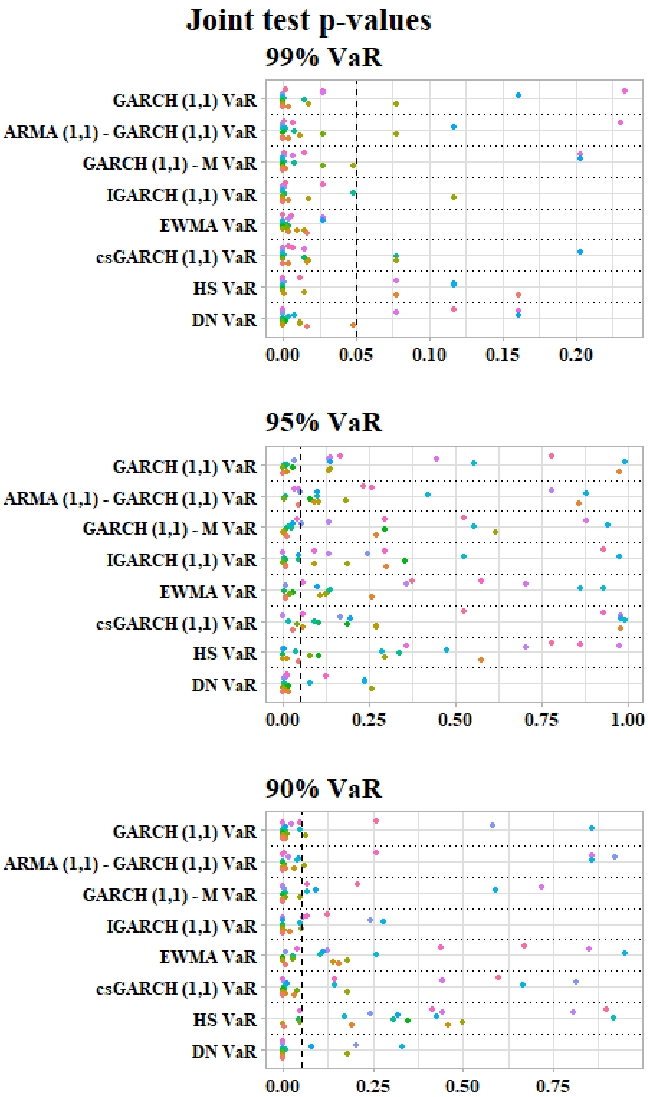

Figure 5. Christoffersen's Interval Forecast test *p*-values. The varying colors of dots are used to symbolize different transportation companies.

The rightmost column lists the specific VaR models that were analyzed using the aforementioned backtesting methods. These models include the GARCH(1,1), ARMA(1,1), IGARCH(1,1), EWMA, and conditional skewness GARCH(1,1) models (csGARCH(1,1)), alongside Historical Simulation (HS) and Delta Normal (DN) models. The table also provides direct references to Figures 2–5, where the empirical results of these backtesting methods are visually depicted.

Particularly, the Historical Simulation (HS) VaR model exhibits a superior alignment with the empirical data, outperforming parametric VaR models in terms of failure rate accuracy and robustness. Such a finding may be indicative of the HS VaR model's flexibility and its ability to better encapsulate the empirical distribution of financial returns without the constraints of specific distributional assumptions.

Within the ambit of GARCH-type VaR models, the csGARCH (1,1) VaR and the Exponentially Weighted Moving Average (EWMA) VaR models emerge as the most efficacious, suggesting that their formulation allows for a more accurate response to market dynamics. On the other hand, the Delta Normal (DN) VaR model's performance is identified as the least compatible with the observed data within this study. This could be a consequence of the DN VaR model's foundational reliance on the normal distribution and constant volatility assumption, which may lead to inflexibility and a lag in adapting to rapid shifts in risk levels, rendering its risk estimates potentially less responsive to real-world market volatility.

In the present study, the generation of Figures 1–5 was meticulously conducted using the R programming language, renowned for its robust capabilities in statistical analysis and data visualization. This sophisticated software environment facilitated the precise computation and graphical representation of the Value-at-Risk (VaR) models' outcomes. R's extensive libraries, particularly those specializing in financial data analysis and econometrics, were utilized to implement the complex GARCH-type and traditional VaR models. The process involved the careful collation and preprocessing of relevant financial data, followed by the application of advanced statistical techniques to calculate the VaR estimates under different model specifications. Subsequently, R's powerful graphical tools were employed to translate these quantitative findings into visually comprehensible figures, effectively illustrating the models' performance and comparative analysis. This methodological approach ensured a high level of accuracy and clarity in depicting the empirical results, thereby providing a solid foundation for this study's subsequent interpretation and discussion.

5. Discussion

In the Discussion Section of our paper, we would like to expand upon several critical aspects that have emerged from our research on the use of GARCH-type Value-at-Risk (VaR) models in Thailand's transportation sector during the COVID-19 pandemic. This discussion aims to provide a broader perspective on the practical implications, potential for investor usage, impact on investment returns, the scope of our research, and the applicability of these models beyond the specific context of the COVID-19 pandemic.

1. Practical Usefulness of Models: While our study primarily utilized statistical tests to assess the effectiveness of various models, their real-world practical utility is of paramount importance. The theoretical robustness of GARCH-type VaR models, as demonstrated in our research, suggests potential effectiveness in actual risk management practices. However, the application of these models in real financial settings might reveal additional insights. Therefore, we propose further research to apply these models in practical scenarios, which will enhance our understanding of their practicality and effectiveness in real-world financial risk management.
2. Use by Investors: The question of whether investors employ GARCH-type VaR models in managing their stock portfolios is significant. While our study demonstrates their theoretical soundness, their actual adoption by investors may vary due to diverse factors such as market conditions, investor risk appetite, and regulatory environments. To better understand the real-world applicability of these models, we recommend conducting empirical research that explores their usage in practical investment scenarios.
3. Impact on Investment Returns: Understanding the correlation between specific risk management models and actual investment returns is essential yet complex. Our future research aims to investigate how different risk management strategies, including the use of GARCH-type VaR models, affect real investment outcomes. This investigation will help elucidate the tangible impact these models have on investment performance.
4. Research Scope and Generalization: Our current research focuses on Thailand's transportation sector during the COVID-19 pandemic. This specific context provides valuable insights but also limits the generalizability of our findings. We acknowledge the necessity of conducting further studies in different sectors or under varying economic conditions. Such broader analyses will enable us to generalize our findings more effectively and understand the versatility of these models across diverse economic landscapes.
5. Model Application Beyond COVID-19: The scope of our study is confined to the market conditions prevalent during the COVID-19 pandemic, which were character-

ized by high volatility and uncertainty. It is crucial to evaluate the performance of GARCH-type VaR models under more stable or 'normal' financial conditions. Future research should focus on assessing these models' effectiveness in various market environments, thereby providing a comprehensive view of their applicability and robustness across different economic cycles.

In conclusion, our research provides a foundational understanding of GARCH-type VaR models in a specific context. However, the above-discussed areas indicate the need for extended research to fully comprehend the broader implications, practical utility, and adaptability of these models in varied financial scenarios.

6. Conclusions

In conclusion, the empirical investigation delineated in this study elucidates the Historical Simulation (HS) VaR model as the most congruent with the actual failure rates, thereby indicating its superior fit. Concurrently, the csGARCH (1,1) VaR and Exponentially Weighted Moving Average (EWMA) VaR models are distinguished by their robustness in volatility forecasting.

Initially, the application of Kupiec's Proportion of Failures (POF) test underscores the HS VaR model's exemplary performance in aligning with the expected failure rates, a trend that is particularly pronounced at the 90% confidence level. The GARCH-type VaR models, while presenting optimal results at the 95% confidence threshold, are observed to underestimate risks at the 99% confidence level and overestimate them at the 90% confidence level. Within the spectrum of GARCH-type models, the EWMA VaR model is recognized for its acute accuracy in failure rate detection. In comparison, the Delta Normal (DN) VaR model's performance is akin to that of the GARCH-type models.

Furthermore, the Independence Test, as formulated by Christoffersen (1998), presents a comparative robustness across the models, suggesting their suitability at a 90% confidence level. However, this test particularly accentuates the robustness of the csGARCH (1,1) VaR and EWMA VaR models.

Additionally, Christoffersen's Interval Forecast test provides insight into the HS VaR model's superior fit while concurrently identifying the DN VaR model as the least compatible option when conditional assessments are considered. The test also reveals the models' optimal performance at a 95% confidence level.

From a managerial perspective, these findings advocate for the adoption of the HS VaR model as a prudent choice for risk management practices within Thailand's Transportation sector. While the GARCH-type VaR models demonstrate utility at the 95% confidence level, there is an opportunity for model refinement, particularly through the careful selection of distributional assumptions for investment return projections. Such enhancements are anticipated to bolster the precision and reliability of these models, thereby augmenting their contribution to rigorous financial risk management.

This empirical study's findings bring forth significant theoretical and practical implications in the realm of financial risk management. Theoretically, it enriches the existing literature on Value-at-Risk (VaR) models, especially under the extraordinary market conditions induced by the COVID-19 pandemic. This study's comparison of GARCH-type VaR models with traditional models in Thailand's transportation sector provides nuanced insights into model efficacy in volatile and unpredictable environments. Practically, the superior performance of the Historical Simulation VaR model, as evidenced by our analysis, offers a pragmatic tool for financial risk managers in similar emerging markets or sectors experiencing high volatility. However, the applicability and generalizability of these findings must be considered through the prism of identified limitations. While the results are immediately relevant to Thailand's transportation sector during the pandemic, their extension to other sectors or more stable economic conditions may require additional investigation. The sector-specific and pandemic-related contextual factors underscore the need for cautious application and potential adaptation in different settings. Future research could thus expand upon this study, exploring the broader applicability of these models in varied economic landscapes and sectors, thereby enhancing the generalizability of the approach and findings.

Author Contributions: Conceptualization, D.L. and L.S.; methodology, D.L. and L.S.; software, D.L. and L.S.; validation, D.L. and L.S.; formal analysis, D.L. and L.S.; investigation, D.L. and L.S.; resources, D.L. and L.S.; data curation, D.L. and L.S.; writing—original draft preparation, D.L. and L.S.; writing—review and editing, D.L. and L.S.; visualization, D.L. and L.S.; supervision, D.L. and L.S.; project administration, D.L. and L.S.; funding acquisition, D.L. and L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors would like to acknowledge the support of the research project from Chiang Mai University Business School.

Conflicts of Interest: The authors declare no conflict of interest.

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