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Forecasting value-at-risk and expected shortfall in emerging market: does forecast combination help?

Trung Hai Le
Vietnam Banking Academy, Hanoi, Vietnam

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Abstract

Purpose – This paper investigates how various strategies for combining forecasts, both simple and optimised approaches, are compared with popular individual risk models in estimating value-at-risk (VaR) and expected shortfall (ES) in emerging market at alternative risk levels.

Design/methodology/approach – Using the case study of the Vietnamese stock market, the author produced one-day-ahead VaR and ES forecast from seven individual risk models and ten alternative forecast combinations. Next, the author employed a battery of backtesting procedures and alternative loss functions to evaluate the global predictive accuracy of the different methods. Finally, the author investigated the relative performance over time of VaR and ES forecasts using fluctuation test.

Findings – The empirical results indicate that, although combined forecasts have reasonable predictive abilities, they are often outperformed by one individual risk model. Furthermore, the author showed that the complex combining methods with optimised weighting functions do not perform better than simple combining methods. The fluctuation test suggests that the poor performance of combined forecasts is mainly due to their inability to cope with periods of instability.

Research limitations/implications – This study reveals the limitation of combining strategies in the one-day-ahead VaR and ES forecasts in emerging markets. A possible direction for further research is to investigate whether this finding holds for multi-day ahead forecasts. Moreover, the inferior performance of combined forecasts during periods of instability motivates further research on the combining strategies that take into account for potential structure breaks in the performance of individual risk models. A potential approach is to improve the individual risk models with macroeconomic variables using a mixed-data sampling approach.

Originality/value – First, the authors contribute to the literature on the forecasting combinations for VaR and ES measures. Second, the author explored a wide range of alternative risk models to forecast both VaR and ES with recent data including periods of the COVID-19 pandemic. Although forecast combination strategies have been providing several good results in several fields, the literature of forecast combination in the VaR and ES context is surprisingly limited, especially for emerging market returns. To the best of the author's knowledge, this is the first study investigating predictive power of combining methods for VaR and ES in an emerging market.

Keywords Value at risk, Expected shortfall, Forecast combination

Paper type Research paper

1. Introduction

The non-normal behaviours of financial markets with extreme observations during the financial crisis and the recent COVID-19 pandemic require enhancing our understandings of risk forecasting toolboxes. Value-at-risk (VaR) and expected shortfall (ER)has been advocated as the standard measures of financial market risks. Whilst VaR is the conditional quantile of financial returns, ES is the conditional expectation of exceedances beyond the VaR. Both measures have been widely used for regulatory tools and internal risk management.

Several methods have been developed to forecast VaR such as the simple historical simulation method, the semi-parametric approach with quantile regression such as the

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conditional autoregressive value-at-risk (CAViaR) model of Engle and Manganelli (2004) or the parametric method via volatility forecasting such as the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) family models from Bollerslev (1987). Forecasting ES is more challenging due to the non-elicitability issue since there is no direct loss function for evaluating ES forecasts. Some approaches have been proposed such as the filter historical simulation (Giannopoulos and Tunaru, 2005), the combination between the VaR models and extreme value theory (EVT) (McNeil and Frey, 2000; Novales and Garcia-Jorcano, 2019) or the recent estimation procedures with joint loss function for VaR and ES of Fissler and Ziegel (2016) (Le, 2020; Patton *et al.*, 2019; Taylor, 2019).

Another approach is the forecast combination from the individual risk models, originated by the seminal work of Bates and Granger (1969). Since there is no consensus about which risk model is best, combining forecasts from a set of individual forecasts can reduce the potential misspecification of individual models and exploit diverse information from different forecasts (Timmermann, 2006).

In this paper, we examined the predictive power of several forecasting combination methods for VaR and ES measures in the Vietnamese stock market. Our paper contributes to the literature in three ways. First, we contributed to the literature on the forecasting combinations for VaR and ES measures. Although forecast combination strategies have been providing several good results in several fields (see, for example, Atiya, 2020; Thomson *et al.*, 2019), the literature of forecast combination in the VaR and ES context is surprisingly limited. Halbleib and Pohlmeier (2012), McAleer *et al.* (2013) and Jeon and Taylor (2013) considered combining method to improve VaR forecasts using quantile regressions, whilst Taylor (2020) and Trucíos and Taylor (2022) are few studies extended the forecast exercises to ES measure to selected developed market and cryptocurrencies. We further explored the potential improvement in forecasting ability of risk forecasting combination methods in emerging markets. The non-normality in financial returns is arguably more pronounced in emerging markets due to non-smooth integration to global markets with higher likelihood of extreme observations (Bekaert *et al.*, 2016; Gu and Ibragimov, 2018). Thus, a good forecasting model in developed markets does not necessary yield accurate forecasts for emerging markets. Moreover, recent extreme market movements, particularly in emerging countries, introduce uncertainty to the accuracy of tail risk models. Thus, forecasting combinations from an ensemble of heterogeneous risk models would potentially improve the forecasting accuracy of VaR and ES in emerging markets. In this study, we focussed our empirical anlysis to the Vietnamese stock market as this country is a typical emerging country that is having rapid economic growth with extensively integration to the global financial markets (Dao and Ngo, 2022).

Second, we explored a wide range of alternative risk models to forecast both VaR and ES with recent data including periods of the COVID-19 pandemic. Our individual risk models include three popular specifications of the GARCH-type models, namely the original GARCH model of Bollerslev (1987) and its asymmetric volatility version GJR-GARCH model of Glosten *et al.* (1993) and the fractionally integrated GARCH (FIGARCH) model of Baillie *et al.* (1996), which captures the long memory of the variance process. The next forecasting method is a class of the observation-driven time series models, which is the generalized autoregressive score (GAS) model of Creal *et al.* (2013), extended to VaR and ES forecasts by Trucíos and Taylor (2022). We also employed three alternative semi-parametric models, including the CAViaR-regression for ES and CAViaR–EVT method proposed by Manganelli and Engle (2004) and the recently developed joint estimation of VaR and ES using asymmetric laplace density (ALD) function of Taylor (2019). We utilized several combining strategies to generate VaR and ES forecasts from individual risk models. We firstly used basic combining methods, including the simple average (AVG), median value (MED), maximum value (MAX) and minimum value (MIN). These simple forecast combinations are fast and easy to compute, yet able to yield very competitive forecasts. We further examined the combining strategies using several scoring functions for VaR and ES recently proposed by Taylor (2020) with minimum and relative scoring weights. To the best of our knowledge, this is the first study investigating predictive power of combining methods for VaR and ES in an emerging market.

Third, we further conducted an extensive analysis to investigate the relative performance of the individual risk models and combined forecasts over time using the fluctuation test of Giacomini and Rossi (2010). Since our sample contains periods of significant instability including the recent COVID-19 pandemic. This analysis allows us to explore the potential hidden information about the performance of risk forecasts in global forecasting comparison exercise.

Our empirical analysis investigates the forecasting abilities of individual risk models and combining strategies in the two leading Vietnamese stock indices, namely VN-Index and HN-Index from 4th January 2006 to 30th January 2023. We used a battery of calibration tests to compare the out-of-sample VaR and ES forecasts as well as comparing their relative performance in terms of minimizing two loss functions.

Overall, we find that the combined forecasts often fail to outperform the individual risk models, neither in calibration tests nor loss function minimization. Only at the 1% risk level for the HNX-Index, we observed superiority of the combining strategies, yet the best performer is the simple averaging method rather than other sophisticated combining strategies. Our fluctuation test reveals that the underperformance of combined forecasting strategies is mainly due to their poor performance during periods of instabilities, particularly the recent COVID-19 pandemic. This may be attributed to the limited diversification of information across the individual risk models in highly volatile periods, which reduces the potential for improved accuracy from forecasting combinations. Other potential reason is the presence of outliers in the return series, which are common in the emerging stock markets. These outliers may adversely affect the estimation of the combining weights in the optimization strategies.

The remainder of the paper is structured as follows: Section 2 describes the individual risk models and Section 3 introduces the combining strategies and backtesting techniques that we employed in our empirical analysis. Section 4 provides our data description and bracketing results whilst section 5 concludes the paper.

2. Methodology

Let $\{r_t\} = \text{In}\left(\frac{p_t}{p_t - 1}\right)$ be the daily continuously compounded return series, where P_t is the closing price of the trading day t. The one-day-ahead VaR of the return series at the α risk level on day t, VaR_t^α, is the $\alpha-$ quantile of the conditional return distribution, estimated using the information available up to time t.

$$VaR_t^\alpha = Sup\{r \in \mathbb{R} : F(r|\mathcal{F}_{t-1}) \leq \alpha\}$$

The ES at the α risk level on day t, ES_t^α, is the expected value of exceedances beyond VaR_t^α:

$$ES_t^\alpha = \boldsymbol{E}(r_t | r_t < VaR_t^\alpha, \mathcal{F}_{t-1})$$

We employ the following individual risk models to produce VaR and ES forecasts.

2.1 Individual VaR and ES forecasting models

2.1.1 GARCH-type models. We considered three alternative specifications of the GARCH-type models, namely the original GARCH (1,1) model from Bollerslev (1987), its asymmetric volatility version GJR-GARCH model of Glosten *et al.* (1993) and the fractionally integrated GARCH (FIGARCH) model of Baillie *et al.* (1996), which captures the long memory of the variance process. Without loss of generality, we modelled the conditional mean of the return series $\{r_t\}$ as follow:

$$r_t = \mu + \sigma_t z_t$$

While the conditional variance process is defined as:

$$\text{GARCH}\,(1,1) : \sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \varphi\,\varepsilon_{t-1}^2$$

$$\text{GJR} - \text{GARCH}\,(1,1) : \sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \varphi\,\varepsilon_{t-1}^2 + \delta\,I_{(\varepsilon_{t-1}<0)}\varepsilon_{t-1}^2$$

$$\text{FI} - \text{GARCH}\,(1,d,1) : \sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \left[1 - \beta L - \varphi L(1-L)^d\right]\varepsilon_t^2$$

where μ is the unconditional mean return, $\varepsilon_t = \sigma_t z_t$ is the residuals from the conditional mean equation, σ_t is the conditional standard deviation and z_t is the series of standardised residuals. $I_{(.)}$ is the indicator function, the parameter δ accounts for the leverage effect in the GJR-GARCH model, L is the lag operator, whilst d is long-memory process parameter. The conditional VaR and ES at the α risk level can be obtained as:

$$\widehat{VaR}_t^\alpha = \widehat{F}_{t-1}^{-1}(\alpha)$$

$$\widehat{ES}_t^\alpha = \frac{1}{\alpha}\int_{-\infty}^{\widehat{VaR}_t^\alpha} x f_{t-1}(x)dx$$

where $\widehat{F}_{t-1}^{-1}(\alpha)$ is the α-quantile of the estimated conditional return distribution and $f_{t-1}(.)$ is the conditional return density function, which is assumed to follow Skew-t distribution to allow for the well-documented asymmetric and fat-tailness of the return distribution (Cont, 2001). Both VaR and ES forecasts can be obtained by numerical approximation and adaptive quadrature numerical integration as detailed by Trucíos and Taylor (2022).

2.1.2 GAS model. The GAS model is developed by Creal *et al.* (2013), which a class of the observation-driven time series models using the score of the conditional distribution instead of the squared returns in the volatility equation.

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \varphi\,s_t\left[\frac{\partial log\,f\left(r_t|\sigma_{t-1}^2\right)}{\partial\sigma_{t-1}^2}\right]$$

where $s_t[.] = \Im_t^{-1}$ is a scaling function for the score, $\Im_t$ is Fisher information and $f(.)$ is the density function of the Skew-t distribution. The specification of the GAS model allows information in the whole distribution to be taken into account, rather only depending on the conditional mean and variance. The VaR and ES forecasts are then computed similar to the GARCH-type models.

2.1.3 The CAViaR models. In contrast to the GARCH-type and GAS models, the CAViaR models produce direct forecasts to the VaR via quantile regression framework as proposed by Engle and Manganelli (2004) without assumptions regarding the conditional return distribution. In this paper, we employed the asymmetric slope specification that can capture the asymmetric effect of positive and negative returns as follows: [1]

$$VaR_t^\alpha = \beta_0 + \beta_1 VaR_{t-1}^\alpha + \beta_2^- I_{(r_{t-1}<0)}|r_{t-1}| + \beta_2^+ I_{(r_{t-1}\geq 0)}|r_{t-1}|$$

where the parameters can be estimated by minimizing the quantile loss function:

$$\frac{1}{T}\sum_{t=1}^{T}\left[\alpha - I_{\left(r_t < VaR_t^{\alpha}\right)}\right]\left[r_t - VaR_t^{\alpha}\right]$$

To forecast ES, we employed three approaches that recently proposed in the literature. First, we follow Manganelli and Engle (2004) to simply scale $\widehat{VaR_t^{\alpha}}$ using estimated parameters from the regression of the exceedances and the corresponding $\widehat{VaR_t^{\alpha}}$. We denote this forecast as CAViaR-Reg.

$$\widehat{ES_t^{\alpha}} = \widehat{\theta}\,\widehat{VaR_t^{\alpha}}$$

Another way to estimate ES is to combine the CAViaR framework with the EVT as proposed by Manganelli and Engle (2004). First, we estimated the CAViaR regression at a threshold level, α_u, which is not as extreme as the risk level α of interest [2]. The standardised quantile residuals $Z_{\alpha_u,t}$ can be obtained as follow:

$$Z_{\alpha_u,t} = \frac{r_t}{\widehat{VaR_t^{\alpha_u}}} - 1$$

where $\widehat{VaR_t^{\alpha_u}}$ is the conditional VaR at the threshold quantile level estimated using the CAViaR regression. Second, we fit the generalized Pareto distribution (GPD) to the $Z_{\alpha_u,t}$ series, i.e. $Z_{\alpha_u,t}^{exceeded} = Z_{\alpha_u,t}\Big|Z_{\alpha_u,t} > 0 \sim GPD(\widehat{\xi},\widehat{\zeta})$, where $\widehat{\xi} < 1$ is the shape parameters and $\widehat{\zeta}$ is the scale parameter of the GPD. The VaR and ES forecast at any risk level $\alpha < \alpha_u$ then can be computed by:

$$VaR_{\alpha}(Z_{\alpha_u,t}) = \frac{\widehat{\zeta}}{\widehat{\xi}}\left[\left(\frac{\alpha T}{T_u}\right)^{-\widehat{\xi}} - 1\right]$$

$$ES_{\alpha}(Z_{\alpha_u,t}) = VaR_{\alpha}(Z_{\alpha_u,t})\left(\frac{1}{1-\widehat{\xi}} + \frac{\widehat{\zeta}}{\left(1-\widehat{\xi}\right)VaR_{\alpha}(Z_{\alpha_u,t})}\right)$$

$$VaR_{\alpha}(r_t) = VaR_{\alpha_u}(r_t)[1 + VaR_{\alpha}(Z_{\alpha_u,t})]$$

$$ES_{\alpha}(r_t) = VaR_{\alpha_u}(r_t)[1 + ES_{\alpha}(Z_{\alpha_u,t})]$$

Taylor (2019) proposes a new method to jointly estimate VaR and ES using the ALD. Motivated by Koenker and Machado (1999), Taylor (2019) show that VaR_t^{α} and ES_t^{α} can be jointly estimated by maximize the likelihood of the ALD density function:

$$f(r_t) = \frac{\alpha - 1}{ES_t^{\alpha}}\exp\left(\frac{\left(r_t - VaR_t^{\alpha}\right)\left(\alpha - 1_{\left(r_t \le VaR_t^{\alpha}\right)}\right)}{\alpha ES_t^{\alpha}}\right)$$

where VaR_t^{α} is computed from the CAViaR regression and ES_t^{α} is linked to the VaR_t^{α} by the following dynamic function to avoid the ES crossing VaR:

$$ES_t^{\alpha} = (1 + \exp(\gamma))VaR_t^{\alpha}$$

2.2 Combining strategies

2.2.1 Simple combining strategies. We firstly employed several basic combining strategies, including the mean, median, maximum and minium values of the individual forecasts. These combination methods are easy to implement, yet providing very competitive forecasts (Genre *et al.*, 2013; Taylor, 2020). Given the M individual risk models, the basic combined forecasts can be obtained as follow:

$$\text{Simple average value (AVG)} : \widehat{RISK}^{\alpha}_{AVG,t} = \sum_{i=1}^{M} \frac{\widehat{RISK}^{\alpha}_{i,t}}{M}$$

$$\text{Median value (MED)} : \widehat{RISK}^{\alpha}_{MED,t} = Med\left\{\widehat{RISK}^{\alpha}_{i,t}\right\}$$

$$\text{Maximum value (MAX)} : \widehat{RISK}^{\alpha}_{MAX,t} = Max\left\{\widehat{RISK}^{\alpha}_{i,t}\right\}$$

$$\text{Minimum value (MIN)} : \widehat{RISK}^{\alpha}_{MIN,t} = Min\left\{\widehat{RISK}^{\alpha}_{i,t}\right\}$$

where $\widehat{RISK}^{\alpha}_{i,t}$ are the forecasting values $\widehat{VaR}^{\alpha}_{i,t}$ and $\widehat{ES}^{\alpha}_{i,t}$ of the individual risk models.

2.2.2 Scoring-based combinations. Taylor (2020) recently develops two combining strategies based on the minimization of the strictly consistent scoring functions proposed by Fissler and Ziegel (2016), in which VaR and ES forecasts are jointly eliciable:

$$S(VaR_t, ES_t) = (I_{r_t \le VaR_t} - \alpha)G_1(VaR_t) - I_{r_t \le VaR_t}G_1(r_t) + G_2(ES_t)\Bigg(ES_t - VaR_t + I_{r_t \le VaR_t} \times \frac{VaR_t - r_t}{\alpha}\Bigg) - \zeta_2(ES_t) + a(r_t) \tag{1}$$

where $G_1(.)$, $G_2(.)$ and $\zeta_2(.)$ are functions, in which $G_1(.)$ and $\zeta_2(.)$ are increasing, $\zeta_2(.)$ is convex and $G_2(.) = \zeta_2{}'(.)$ [3].

The individual forecasts can be combined using two strategies, namely the relative score combining (RSC) and minimum score combining (MSC) methods.

In the RSC method, the combined estimators can be obtained by:

$$\widehat{RISK}^{\alpha}_{RSC,t} = \sum_{i=1}^{M} w_i \widehat{RISK}^{\alpha}_{i,t}$$

$$w_i = \frac{exp\left(-\lambda \sum_{j=1}^{t-1} S\left(\widehat{VAR}_{ij}, \widehat{ES}_{ij}, r_j\right)\right)}{\sum_{K=1}^{M} exp\left(-\lambda \sum_{j=1}^{t-1} S\left(\widehat{VAR}_{ij}, \widehat{ES}_{ij}, r_j\right)\right)}$$

where $S(.)$ is the chosen scoring function, $\lambda > 0$ is the tuning parameter that minimizes the sum of the in-sample values of $S(.)$. A value of λ close to zero leads to the combined values similar to the simple average method, while a large value of λ would collapse the combining values to the individual forecasts with the lowest in-sample value of the scoring function.

The MSC method is relatively more complicated since the combining weights are estimated separately for VaR and ES.

$$\widehat{VaR^{\alpha}_{MSC,t}} = \sum\nolimits_{i=1}^{M} w_{i,VaR}\widehat{VaR^{\alpha}_{i,t}}$$

$$\widehat{ES^{\alpha}_{MSC,t}} = \widehat{VaR^{\alpha}_{i,t}} + \sum\nolimits_{i=1}^{M} w_{i,ES}\left(\widehat{ES^{\alpha}_{i,t}} - \widehat{VaR^{\alpha}_{i,t}}\right)$$

where the combining weights, $w_{i,VaR}$ and $w_{i,ES}$, are obtained by minimizing the chosen scoring function in each in-sample VaR and ES, subject to the constraints, $w_{i,}$ VaR, $w_{i,ES} > 0, \sum\nolimits_{i=1}^{M} w_{i,VaR} = 1, \sum\nolimits_{i=1}^{M} w_{i,ES} = 1$. See Taylor (2022) for further details on the estimation strategy of the combining weights.

2.3 Backtesting methods

We implement a battery of popular calibration tests to check the performance of VaR and ES forecasts, including the conditional coverage test (CC) of Christoffersen (1998), the dynamic quantile (DQ) test of Engle and Manganelli (2004), the VaR quantile regression test (VQ) of Gaglianone *et al.* (2011), the exceedance residuals (ER) test of McNeil and Frey (2000), the conditional calibration (CoC) test of Nolde and Ziegel (2017) and the exceedance shortfall regression (ESR) of Bayer and Dimitriadis (2022) [4]. Whilst the first three tests are used to evaluate VaR forecasts, the next three tests examined the efficiency of both VaR and ES forecasts. These tests can be applied to evaluate the absolute performance of the VaR and ES forecasts, in which the risk models are correctly specified with regards to the chosen quantile levels.

We also investigated the relative performance of VaR and ES forecasts. In particular, models that generate the lowest value of the scoring functions are arguably preferred over those with higher loss values. First, we used the popular quantile loss function to compare VaR forecasts as suggested by Giacomini and Komunjer (2005). Second, we employed several scoring functions belonging to the family functions as in Eq. (1) to jointly examine the VaR and ES forecasts, namely the FZG, NZ and AL loss functions as specified in Table 1.

3. Empirical results

3.1 Data

We evaluate the predictive ability of one-day-ahead VaR and ES forecast for the two main Vietnamese stock indices, namely VN-Index and HNX-Index for the 1 and 5% risk levels, which are frequently used in the literature and regulatory requirements. Our data are publicly collected from the website Investing.com, spanning the period from 3 January 2006 to 31 January 2023.

Table 2 provides summary statistics of the daily returns for VN-Index and HNX-Index. The unconditional mean of daily return is close to zero for both indices. HNX-Index exhibits

	$G_1(x)$	$G_2(x)$	$\zeta_2 0(x)$	$a(.)$
FZG (Fissler *et al.*, 2016)	x	$\exp(x)/(1+\exp(x))$	$\ln(1+\exp(x))$	ln(2)
NZ (Nolde *et al.*, 2017)	0	$0.5(-x)^{-0.5}$	$-(-x)^{0.5}$	0
AL	0	$-1/x$	$-\ln(-x)$	$1-\ln(1-\alpha)$

Note(s): This table provides specifications of alternative scoring functions to jointly evaluate VaR and ES forecasts
Source(s): Author's own work

Table 1.
Functions used in Eq (1) to form scoring functions

relatively higher volatility with the standard deviation at 0.018, compared to 0.015 for VN-Index. The former also reports more extreme observations with the minimum value at −0.129 and maximum value at 0.097. Both series are characterised by negative skewness and leptokurtic distributions, as indicated by the skewness and kurtosis coefficients. Indeed, the Jarque–Bera test statistics are very large and significantly reject normality in the return distribution. Figure 1 displays the evolution of the daily closing prices and returns of the two indices. This observation justifies the choice of Skew-t distribution in the GARCH-type and GAS models as this distribution could allow for non-zero skewness and fat-tailness in the conditional return distribution.

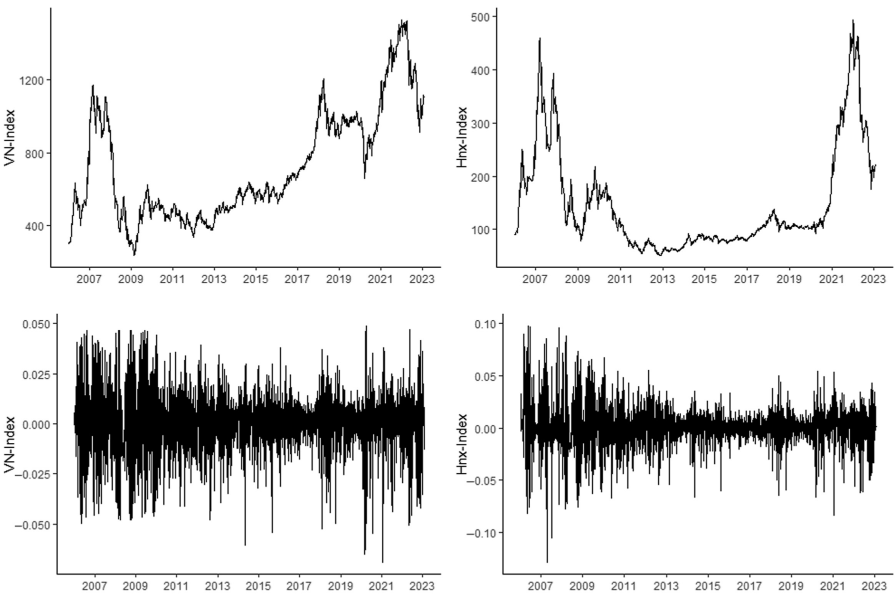
3.2 Out-of-sample results

We focussed on the out-of-sample VaR and ES forecasts in our empirical analysis. To this end, we employed a rolling window approach with a fixed length of 1.250 observations or equivalently to five years. In particular, we estimated all individual forecasting method

	Mean	Min	Median	Max	Std dev	Skewness	Kurtosis	Jarque–Bera
VNI	0.0003	−0.069	0.001	0.049	0.015	−0.34	1.83	675.423
HNX	0.0002	−0.129	0.0005	0.097	0.018	−0.168	4.372	3378.542

Note(s): This table provides descriptive statistics of daily returns of VNI-Index and HNX-Index. Statistics include the mean, median, minimum, maximum, standard deviation, skewness and kurtosis coefficients. The last column reports the Jarque-Bera test statistics for normality of the daily returns
Source(s): Author's own work

Table 2. Descriptive statistics of daily returns



Note(s): This figure presents the dynamics of Vn-Index and HNX-Index. The top panel provides the change in the index prices, while the bottom panel is the return of the indices from 1/2006 to 1/2023
Source(s): Authors' own work

Figure 1. Daily prices and returns of VN-Index and HNX-Index

using an estimation window of 1.250 daily returns and obtain the VaR and ES forecasts for the one-day-ahead for all quantile levels with estimated parameters. These in-sample VaR and ES are also used to estimate the weighting functions for scoring-based combining method, whilst the out-of-sample VaR and ES are used to form the simple combining forecasts. We then moved one day forward to re-estimates all the model parameters and iterate this procedure until the end of the sample. In total, we have 2,260 estimation windows and out-of-sample VaR and ES for VN-Index and HNX-Index.

3.2.1 Out-of-sample results for VN-Index. Table 3 reports the calibration test results of the one-day-ahead VaR and ES forecasts for the VN-Index by all individual risk models and combining strategies. For the 1% risk level, the hit values indicate that almost all risk models underestimate the risk level VN-Index, except only for the MAX combination method. GAS and MIN are the worst performer as these methods significantly underestimate the risks in VN-Index and do not pass any calibration tests. On the other hand, FIGARCH delivers the best VaR and ES forecasts as this model is the only procedures passing all the tests at the 1% risk level. Interestingly, none of the combining strategies manage to deliver satisfactory calibration test results as they reject the null hypothesis of correctly specified forecasts at the 5% significance-level in at least one test. For the 5% risk-level, almost all the procedures deliver satisfactory backtesting results, except for only two individual risk models (GAS and CAViaR-Reg) and two combining strategies (MIN and MAX).

Next, we compared the forecast losses of the one-day-ahead VaR and ES using the loss functions presented in Table 4. In each column, the forecasting strategy that generates the lowest loss value is highlighted in italic, whilst the second-best performer is highlighted in italic numbers. Interestingly, we found that the combining methods never provide the best performance in all loss functions and risk levels. For the 1% risk level, FIGARCH model yields the best result as this model provides the lowest forecasting losses in all fourloss functions. The simple AVG combining method comes at the second-best place in 3 out 4 loss functions, only except for the AAL loss function with the AL-MSC method. For the 5% risk-level, the GJR model produces the lowest loss scores in the first three loss functions, whilst FIGARCH takes the first place in the AAL function. The two optimized combining methods, FZG–MSC and AL–RSC forecasts, comes at the second place, respectively.

We further compared the relative superiority of the forecasting methods using the fluctuation test of Giacomini and Rossi (2010) as the forecasting performance of the risk models can change over time, especially during the periods with high volatility. Figures 2 and 3 compared the relative performance over time between FIGARCH and the two best combining procedures, namely AVG and AL–MSC procedures. The figures show the differences in the scoring functions of FIGARCH and its corresponding competitors. A negative fluctuation statistic indicates that the first model (FIGARCH) outperforms the second forecast (i.e. AVG and AL–MSC combining strategies) in each pairwise comparison for that period of time [5]. We find that the FIGARCH forecast outperforms the two combined procedures mainly during 2018 and particularly the recent COVID-19 pandemic, which are marked with significant volatility in the Vietnamese stock market. As point out by Taylor (2019), including a poor forecasting method in a combination would have adverse impacts on the accuracy due to the increasing the parameter estimation error. Thus, these results indicate that the underperformance of combined forecasting strategies seem to be resulted from the poor performance of the individual risk models during the periods of instability [6].

3.2.2 Out-of-sample results for HNX-Index. The calibration test results for the one-day-ahead VaR and ES forecasts of the HNX-Index by different forecasting methods are shown in Table 5. At the 1% risk-level, the GAS and MIN models fail to pass any calibration tests and significantly underestimate the HNX-Index risk. The other models perform satisfactorily as

		Hits	UC	CC	DQ	VQ	ER	CC	ESR	Total reject
Panel A: Risk level 1%										
Individual risk models	GARCH	1,372	0.093	0.182	0.421	0.239	0.291	0.290	0.047	1
	GJR	1,372	0.093	0.182	0.454	0.157	0.327	0.294	0.032	1
	GAS	2,655	0.000	0.000	0.000	0.000	0.000	0.000	0.000	7
	FIGARCH	1,416	0.061	0.135	0.361	0.195	0.463	0.246	0.068	*0*
	CAViaR-Reg	1,372	0.093	0.049	0.027	0.308	0.253	0.222	0.088	2
	CAViaR–EVT	1,416	0.061	0.135	0.272	0.142	0.668	0.202	0.026	1
	CAViaR–ALD	1,239	0.271	0.078	0.006	0.443	0.532	0.553	0.338	1
Combining forecasts	AVG	1,46	0.040	0.097	0.210	0.349	0.385	0.190	0.050	1
	MED	1,327	0.136	0.237	0.522	0.279	0.287	0.362	0.048	1
	MAX	0.885	0.575	0.715	0.975	0.004	0.592	0.527	0.282	1
	MIN	2,92	0.000	0.000	0.000	0.000	0.000	0.000	0.000	7
	FZG–MSC	1,416	0.061	0.039	0.008	0.324	0.410	0.244	0.052	1
	NZ–MSC	1,327	0.136	0.059	0.009	0.615	0.379	0.395	0.090	1
	AL–MSC	1,327	0.136	0.059	0.006	0.567	0.509	0.370	0.276	1
	FZG–RSC	1,327	0.136	0.059	0.011	0.272	0.586	0.300	0.110	1
	NZ–RSC	1,327	0.136	0.059	0.007	0.456	0.546	0.396	0.102	1
	AL–RSC	1,327	0.136	0.059	0.010	0.536	0.594	0.382	0.143	1
Panel B: Risk level 5%										
	GARCH	5,177	0.701	0.677	0.974	0.891	0.230	0.313	0.249	*0*
	GJR	4,779	0.627	0.886	0.931	0.769	0.110	0.067	0.257	*0*
	GAS	6,504	0.002	0.001	0.000	0.000	0.000	0.000	0.000	3
	FIGARCH	5,088	0.847	0.873	0.991	0.889	0.216	0.290	0.298	*0*
	CAViaR-Reg	5,310	0.503	0.465	0.624	0.662	0.020	0.025	0.032	3
	CAViaR–EVT	5,619	0.185	0.233	0.279	0.401	0.275	0.325	0.128	*0*
	CAViaR–ALD	5,310	0.503	0.166	0.328	0.671	0.431	0.734	0.279	*0*
Combining forecasts	AVG	4,956	0.923	0.965	0.931	0.800	0.067	0.115	0.137	*0*
	MED	5,088	0.847	0.873	0.966	0.961	0.099	0.164	0.223	*0*
	MAX	3,850	0.009	0.001	0.088	0.000	0.347	0.017	0.004	2
	MIN	7,876	0.000	0.000	0.000	0.002	0.000	0.000	0.000	3
	FZG–MSC	4,956	0.923	0.820	0.960	0.958	0.118	0.119	0.173	*0*
	NZ–MSC	5,265	0.566	0.662	0.863	0.772	0.125	0.275	0.129	*0*
	AL–MSC	5,354	0.445	0.456	0.780	0.709	0.334	0.558	0.224	*0*
	FZG–RSC	4,823	0.698	0.878	0.973	0.916	0.100	0.131	0.081	*0*
	NZ–RSC	4,823	0.698	0.878	0.974	0.920	0.320	0.520	0.235	*0*
	AL–RSC	4,735	0.559	0.843	0.992	0.906	0.274	0.397	0.297	*0*

Note(s): This table reports the calibration test results of the one-day-ahead VaR and ES forecasts for the VN-Index by all individual risk models and combining strategies. The first column presents the realized violation rate of the VaR forecasts. The next four columns are the *p*-value of the VaR backtesting results while the next three columns provide the *p*-value of the calibration tests for both VaR and ES forecasts. The last column reports the total rejections of the forecasting procedures over all calibration test. The best methods with satisfactory forecasting performance are those are not failed any tests are highlighted in italics. Panel A are results for the 1% risk level, while Panel B is the 5% risk level
Source(s): Author's own work

Table 3. One-day ahead backtesting results for VN-Index at the 1 and 5% risk levels

the hits values are close to 1% and there are no test rejections in 14 out of 17 risk models. The performances of risk models are more diverse at the 5% risk level. Only three risk models (GARCH, GJR and FIGARCH) and five combining strategies (AVG, MED, FZG–MSC, NZ–RSC and AL–RSC) pass all calibration tests.

We further apply the loss functions to assess the forecasting performance of the one-day-ahead VaR and ES of the HNX-Index in Table 6. The best and second-best forecasting strategies for each loss function and risk level are highlighted in italic and

Table 4.
One-day-ahead VaR and ES forecast losses VN-Index at the 1 and 5% risk levels

		Panel A: Risk level 1%				Panel B: Risk level 5%			
		AQL	AFZG	ANZ	AAL	AQL	AFZG	ANZ	AAL
Individual risk models	GARCH	0.455	22,772	21,159	−210,536	1,435	15,485	16,617	−256,529
	GJR	0.452	22,605	21,126	−210,19	*1,425*	*15,373*	*16,561*	−257,010
	GAS	0.573	28,67	25,447	−144,437	1,574	16,978	17,626	−238,670
	FIGARCH	*0.447*	*22,341*	*20,923*	*−213,19*	1,433	15,462	16,581	*−257,289*
	CAViaR-Reg	0.459	22,961	21,267	−209,017	1,460	15,755	16,818	−253,068
	CAViaR–EVT	0.459	22,979	21,294	−208,639	1,460	15,759	16,781	−254,239
	CAViaR–ALD	0.453	22,641	21,071	−211,487	1,449	15,639	16,691	−255,736
Combining forecasts	AVG	*0.449*	*22,48*	*21,048*	−211,167	1,432	15,452	16,603	−256,525
	MED	0.452	22,599	21,089	−211,03	1,433	15,465	16,606	−256,601
	MAX	0.478	23,854	21,395	−210,479	1,535	16,542	16,990	−253,705
	MIN	0.553	27,708	25,221	−144,693	1,498	16,178	17,377	−240,168
	FZG–MSC	0.456	22,814	21,229	−209,182	*1,425*	*15,379*	16,571	−256,769
	NZ–MSC	0.458	22,913	21,264	−208,99	1,444	15,579	16,675	−255,585
	AL–MSC	0.453	22,67	21,082	*−211,536*	1,439	15,524	16,635	−256,273
	FZG–RSC	0.457	22,857	21,187	−210,11	1,426	15,392	16,608	−255,974
	NZ–RSC	0.456	22,837	21,22	−209,396	1,427	15,396	16,573	−257,004
	AL–RSC	0.454	22,737	21,129	−210,849	1,426	15,386	*16,565*	*−257,138*

Note(s): This table reports the average values of the loss functions for the one-day-ahead VaR and ES forecasts for the VN-Index by all individual risk models and combining strategies. Panel A are results for the 1% risk level, while Panel B is the 5% risk level. AQL is the quantile loss function, while AFZG, ANZ and AAL are the loss functions to jointly evaluate VaR and ES forecasts with the formulations are presented in Table 2. Best method with the lowest loss value for each loss function is highlighted in italic, while the second-best method is highlighted in italic underlined
Source(s): Author's own work

italic numbers respectively. As with the VN-Index, the optimized combining strategies are not superior at both risk levels. At the 1% risk level, the lowest loss values are obtained by the two simple combining strategies, namely AVG and MED, followed by the FIGARCH model. At the 5% risk-level, the GJR model outperforms all other models in all four loss functions, whilst the AL–RSC combined method and the GARCH model rank second in two loss functions each. Figure 4 compares the relative performance over time between the GJR model and the best combining method, AL–RSC procedures for the 5% risk model [7] Similar to the results of VN-Index, the superiority of the GJR model mainly comes from the instability periods, particularly during the recent COVID-19 pandemic. The reason for this may be that the optimized combining methods depend on the weights assigned to each model, which may not capture the true contribution of each model to the forecast.

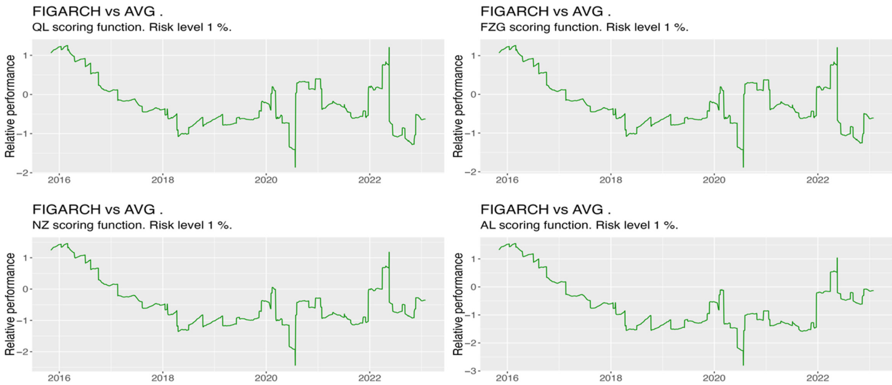


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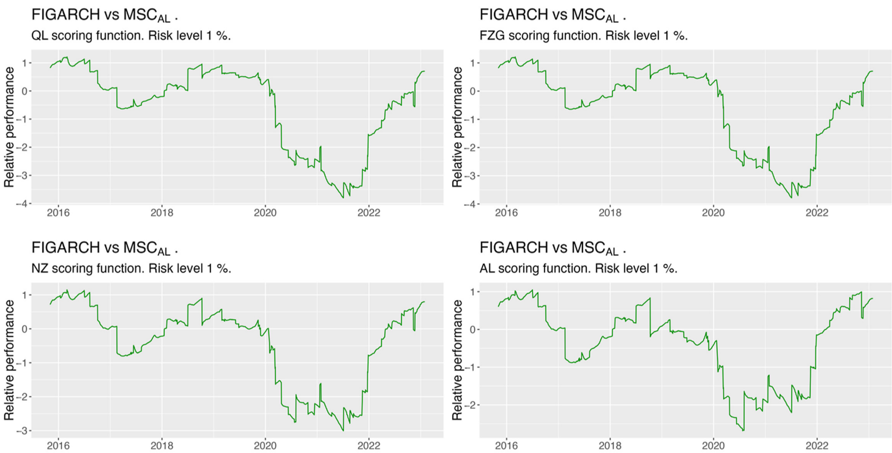
Figure 2.
Relative superiority comparing the 1% VaR and ES forecasts for VN-Index of the FIGARCH model and AVG combining strategy in four scoring functions



Source(s): Authors' own work

Figure 3.
Relative superiority comparing the 1% VaR and ES forecasts for VN-Index of the FIGARCH model and MSC–AL combining strategy in four scoring functions

		Hits	UC	CC	DQ	VQ	ER	CC	ESR	Total reject
Panel A: Risk level 1%										
Individual risk models	GARCH	1,150	0.484	0.463	0.831	0.579	0.240	0.614	0.843	*0*
	GJR	1,238	0.272	0.359	0.744	0.297	0.251	0.520	0.425	*0*
	GAS	2,477	0.000	0.000	0.000	0.000	0.000	0.000	0.000	7
	FIGARCH	1,061	0.771	0.503	0.840	0.535	0.192	0.762	0.235	*0*
	CAViaR-Reg	0.929	0.731	0.398	0.506	0.495	0.214	0.638	0.331	*0*
	CAViaR–EVT	1,238	0.272	0.078	0.048	0.490	0.696	0.563	0.968	1
	CAViaR–ALD	1,017	0.934	0.489	0.496	0.410	0.452	0.748	0.193	*0*
Combining methods	AVG	1,106	0.619	0.493	0.838	0.641	0.400	0.820	0.617	*0*
	MED	1,017	0.934	0.489	0.840	0.526	0.155	0.505	0.873	*0*
	MAX	0.619	0.050	0.135	0.787	0.031	0.550	0.057	0.057	1
	MIN	2,875	0.000	0.000	0.000	0.000	0.006	0.000	0.000	7
	FZG–MSC	0.885	0.574	0.332	0.540	0.119	0.256	0.623	0.460	*0*
	NZ–MSC	0.929	0.731	0.398	0.658	0.496	0.279	0.874	0.527	*0*
	AL–MSC	0.973	0.897	0.453	0.591	0.724	0.313	0.991	0.398	*0*
	FZG–RSC	0.885	0.574	0.332	0.647	0.897	0.147	0.091	0.920	*0*
	NZ–RSC	0.929	0.731	0.398	0.643	0.878	0.219	0.427	0.676	*0*
	AL–RSC	0.929	0.731	0.398	0.651	0.872	0.168	0.630	0.489	*0*
Panel B: Risk level 5%										
Individual risk models	GARCH	5,396	0.394	0.089	0.183	0.799	0.404	0.530	0.386	*0*
	GJR	5,263	0.569	0.161	0.326	0.891	0.336	0.560	0.376	*0*
	GAS	6,413	0.003	0.009	0.001	0.001	0.000	0.001	0.000	7
	FIGARCH	5,352	0.448	0.169	0.485	0.790	0.393	0.651	0.463	*0*
	CAViaR-Reg	5,838	0.075	0.019	0.069	0.282	0.323	0.181	0.162	1
	CAViaR–EVT	6,236	0.009	0.004	0.026	0.034	0.589	0.052	0.293	4
	CAViaR–ALD	5,838	0.075	0.036	0.211	0.373	0.675	0.217	0.489	1
Combining methods	AVG	5,484	0.298	0.167	0.449	0.315	0.313	0.424	0.299	*0*
	MED	5,440	0.344	0.170	0.444	0.304	0.336	0.508	0.358	*0*
	MAX	4,202	0.074	0.037	0.382	0.002	0.640	0.109	0.073	2
	MIN	7,917	0.000	0.000	0.000	0.000	0.000	0.000	0.000	7
	FZG–MSC	5,440	0.344	0.170	0.408	0.315	0.237	0.347	0.191	*0*
	NZ–MSC	6,015	0.032	0.041	0.208	0.195	0.483	0.126	0.240	2
	AL–MSC	6,015	0.032	0.041	0.209	0.217	0.463	0.125	0.271	2
	FZG–RSC	5,617	0.186	0.045	0.106	0.191	0.437	0.400	0.314	1
	NZ–RSC	5,661	0.157	0.141	0.332	0.147	0.619	0.396	0.457	*0*
	AL–RSC	5,661	0.157	0.141	0.384	0.161	0.655	0.394	0.444	*0*

Note(s): This table reports the calibration test results of the one-day-ahead VaR and ES forecasts for the HNX-Index by all individual risk models and combining strategies. The first column presents the realized violation rate of the VaR forecasts. The next four columns are the *p*-value of the VaR backtesting results while the next three columns provide the *p*-value of the calibration tests for both VaR and ES forecasts. The last column reports the total rejections of the forecasting procedures over all calibration tests. The best methods with satisfactory forecasting performance are those are not failed any tests are highlighted in italics. Panel A are results for the 1% risk level, while Panel B is the 5% risk level
Source(s): Author's own work

Table 5.
One-day-ahead backtesting results for HNX-Index at the 1 and 5% risk levels

4. Conclusion

In this paper, we compared the predictive performance of several combining forecast strategies, including both simple and optimized procedures, with popular individual risk models in producing VaR and ES forecast for Vietnamese stock returns in two risk levels. Using a battery of backtesting procedures and alternative loss functions, we found that although combining forecast strategies yield reasonable predictability, they were often outperformed by one individual risk model. Furthermore, the simple equal-weighted

Table 6. One-day-ahead VaR and ES forecast losses HNX-Index at the 1 and 5% risk levels

		Panel A: Risk level 1%				Panel B: Risk level 5%			
		AQL	AFZG	ANZ	AAL	AQL	AFZG	ANZ	AAL
Individual risk models	GARCH	0.479	23,876	21,447	−210,097	1,552	16,649	*17,085*	*−252,929*
	GJR	0.481	23,966	21,490	−209,708	*1,540*	*16,519*	*17,014*	*−253,758*
	GAS	0.557	27,752	23,861	−177,503	1,666	17,879	17,836	−241,099
	FIGARCH	0.477	23,759	21,411	−210,154	1,560	16,738	17,137	−252,219
	CAViaR-Reg	0.479	23,838	21,471	−209,102	1,582	16,980	17,276	−250,479
	CAViaR–EVT	0.483	24,046	21,480	−210,145	1,577	16,924	17,239	−251,021
	CAViaR–ALD	0.490	24,414	21,756	−206,571	1,573	16,884	17,241	−250,686
Combining methods	AVG	*0.470*	*23,418*	*21,227*	*−212,257*	1,558	16,710	17,111	−252,639
	MED	*0.475*	*23,627*	*21,312*	*−211,492*	1,557	16,706	17,119	−252,459
	MAX	0.509	25,307	21,957	−206,209	1,629	17,468	17,386	−250,364
	MIN	0.543	27,086	23,755	−177,026	1,612	17,306	17,675	−241,909
	FZG–MSC	0.481	23,946	21,494	−209,504	1,558	16,719	17,133	−252,220
	NZ–MSC	0.482	23,978	21,516	−209,296	1,572	16,863	17,211	−251,234
	AL–MSC	0.484	24,111	21,590	−208,462	1,571	16,855	17,206	−251,289
	FZG–RSC	0.478	23,808	21,430	−210,128	1,557	16,700	17,117	−252,465
	NZ–RSC	0.482	23,980	21,506	−209,592	1,555	16,685	17,112	−252,471
	AL–RSC	0.480	23,898	21,489	−209,551	*1,551*	*16,643*	17,095	−252,581

Note(s): This table reports the average values of the loss functions for the one-day-ahead VaR and ES forecasts for the VN-Index by all individual risk models and combining strategies. Panel A are results for the 1% risk level, whilst Panel B is the 5% risk level. AQL is the quantile loss function, whilst AFZG, ANZ and AAL are the loss functions to jointly evaluate VaR and ES forecasts with the formulations are presented in Table 2. Best method with the lowest loss value for each loss function is highlighted in italic, whilst the second-best method is highlighted in italic underlined

Source(s): Author's own work

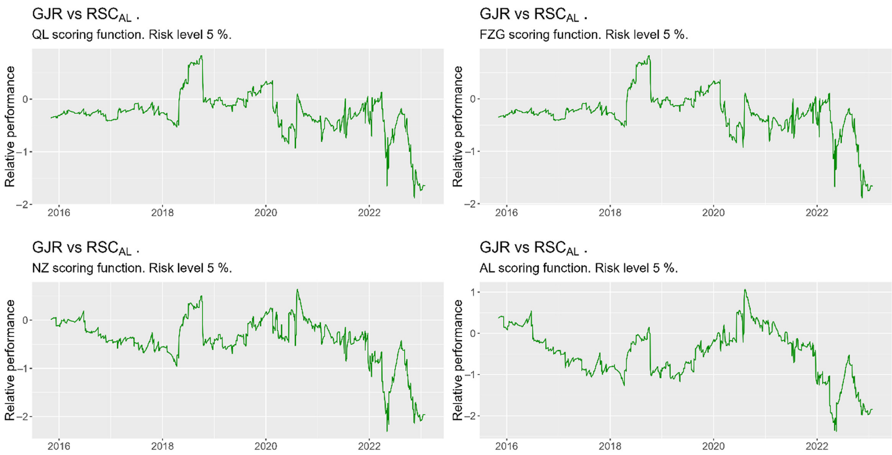


Figure 4.
Relative superiority comparing the 5% VaR and ES forecasts for HNX-Index of the GJR model and RSC–AL combining strategy in four scoring functions

Source(s): Authors' own work

approach appears to outperform the complex combination techniques in terms of VaR and ES estimation. Our fluctuation test indicates that the poor performance of combined forecasting strategies is attributable to their failure to capture periods of turbulence, especially during the recent COVID-19 pandemic. Moreover, the presence of outliers, which are common in emerging market returns, potentially distort the accuracy and reliability of information from individual risk models. This limitation in the diversity of information potentially leads to errors in the optimized weights of combining strategies. This result is in line with Trucíos and Taylor (2022) in the case of VaR and ES forecasts for cryptocurrencies.

Our research reveals the limitation of combining strategies in the one-day-ahead VaR and ES forecasts in the emerging markets. A possible direction for further research is to investigate whether this finding holds for multi-day-ahead forecasts. Moreover, the inferior performance of combined forecasts during periods of instability motivates further research on the combining strategies that take into account for potential structure breaks in the performance of individual risk models. A potential approach is to improve the individual risk models with macroeconomic variables (Engle *et al.*, 2013) using the mixed-data sampling approach (Le, 2020).

Notes

1. There is also an absolute value specification of the CAViaR model that does not take into account the leverage effect in Engle and Managenelli. However, the author only employed the asymmetric specification in this paper due to superior performance in the stock markets as documented in Taylor (2019) or Le (2020).
2. Similar to Manganelli and Engle (2004), the author chose the threshold level at $a_u = 7.5\%$
3. Details on the family of the scoring functions can be see in Fissler and Ziegel (2016).
4. Given the limit of space, the author do not provide details on the explanation of these tests. The details of these tests can be referred from Nieto and Ruiz (2016) and Hallin and Trucíos (2021).
5. Other pairwise comparisons are not reported here to save places but available from the authors upon requests.
6. To save space, the author do not report the fluctuation test for the 5% VaR and ES forecasts since the results are similar to the 1% risk level. The figures are available from the author upon requests.

7. Other pairwise comparisons are not reported here to save places but available from the author upon requests. To save space, the author do not report the fluctuation test for the 1% VaR and ES forecasts since the results are similar to the 5% risk level. The figures are available from the author upon requests.

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About the author

Trung Hai Le is Full-Time Lecturer at the Banking Faculty, Banking Academy of Vietnam. He holds Ph.D. from the Norwich Business School, University of East Anglia, UK and M.Sc from the Economic School, University of Leicester, UK. He is a Certified FRM (Financial Risk Manager) of the Global Association of Risk Professionals. His research interests are financial modelling, financial risk management, financial institutions and systemic risks. He has published in several high-reputational journals such as *International Journal of Forecasting*, *Financial Research Letter*, *International Journal of Emerging Markets*, *International Journal of Economic and Finance*. Trung Hai Le can be contacted at: trunglh@hvnh.edu.vn