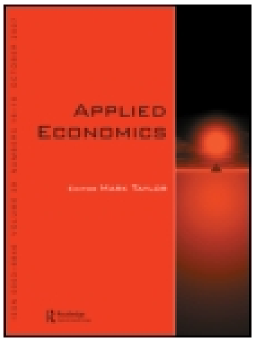

Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

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To cite this article: Chung-Chu Chuang, Yi-Hsien Wang, Tsai-Jung Yeh & Shuo-Li Chuang (2015) Hedging effectiveness of the hedged portfolio: the expected utility maximization subject to the value-at-risk approach, Applied Economics, 47:20, 2040-2052, DOI: 10.1080/00036846.2014.1000528

To link to this article: https://doi.org/10.1080/00036846.2014.1000528

Applied Economics, 2015
Vol. 47, No. 20, 2040–2052, http://dx.doi.org/10.1080/00036846.2014.1000528

Hedging effectiveness of the hedged portfolio: the expected utility maximization subject to the value-at-risk approach

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Multivariate volatilities and distribution play an important role in portfolio selection and can be used to calculate the value-at-risk (VaR) of a multiple-asset financial position. This study proposes a new expected utility maximization (EUM) model that accounts for VaR (EUM model with a VaR constraint (EUM–VaR)). Additionally, using the EUM–VaR model, this study investigates the hedging effectiveness of short and long hedged portfolios constructed with multivariate generalized autoregressive conditional heteroscedasticity (GARCH)-type models that feature level effects and multivariate normal *t* and skewed *t* distributions for stock indexes and their corresponding futures in the Greater China Region. It is found that, all else equal, portfolios constructed using the multivariate skewed *t* distribution are far more effective in hedging than those that rely on the other distributions, and the effectiveness of hedged portfolios from the multivariate GARCH-type models with level effects outperform those without level effects. Additionally, the effectiveness of hedged portfolios from multivariate asymmetric GARCH-type models exceeds that of those from multivariate symmetric GARCH-type models. Thus, investors should select the multivariate asymmetry in volatility, multivariate asymmetry in distribution, and EUM–VaR models to construct effectively hedged portfolios. The results of this study can provide useful implications for investors looking to manage risk.

Keywords: expected utility maximization; value-at-risk; GARCH; VEC–ADVECH; hedging effectiveness; futures

JEL Classification: G11; G32; C13; C32

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I. Introduction

Stock index futures (which are derived from stock indexes) are one of the most widely hedging instruments of investors. Since stock indexes are closely related to their corresponding futures, it is necessary to hedge for associated risk. In recent years, there have been a large number of dramatic (or sensational or climactic) events that have greatly affected the volatility of the world's financial markets, and as such, effective risk management has become a growing concern for investors.

From the viewpoint of investors, value-at-risk (VaR) can be defined as the maximum loss of a financial position or portfolio during a given time period for a given confidence level. According to this view, one treats VaR as a measure of loss associated with a rare (or extraordinary) event under normal market conditions. It is a simple concept, which can be used to effectively quantify market risk, and as such, it is a commonly used tool. In 1996, the Basel Committee on Banking Supervision proposed amendments to the Basel Accord that added market risk to financial institutions' capital adequacy requirements (in order to improve bank capital provisions) and stipulated that VaR ought to be used as an indicator of said risk.

Portfolio managers have often determined portfolio positions using a mean-VaR optimality criterion. However, a need to consider the trade-off between portfolio returns and risk led to the development of the expected utility maximization (EUM) model, which can simultaneously account for a the portfolio manager's risk aversion and the portfolio's returns and variance. Some studies have utilized the EUM model to determine the appropriate hedge ratio of each asset in a portfolio (Cecchetti *et al.*, 1988; Hsln *et al.*, 1994; Chang, 2011). However, the EUM model is unable to control for the maximum possible loss within a decision-maker's tolerable range; thus, it is necessary to include a constraint on VaR. However, it is quite uncommon to use an EUM model with a VaR constraint (hereafter abbreviated as EUM–VaR) to decide the hedge ratio of each asset in a portfolio.

How the distribution of financial asset returns is fitted significantly affects risk managers' decision-making and asset allocation in hedged portfolios. The distribution of financial asset returns is known to be non-Gaussian (Mandelbrot, 1963; Fama, 1965; Bollerslev, 1987) and to have heavier tails than what is observed in a normal distribution. These features indicate more extreme values, which have serious implications for risk management. When the distribution of asset returns has heavy tails, the *t* distribution outperforms the normal distribution in VaR backtesting (Bauwens and Laurent, 2005; Angelidis and Benos, 2008; Chuang *et al.*, 2012). However, the *t* distribution cannot capture the asymmetry in the financial asset returns distribution. As such, some studies utilized the skewed *t* distribution to estimate VaR and found that it outperformed the *t* distribution in backtesting (Bauwens and Laurent, 2005; Angelidis and Benos, 2008; Mabrouk and Aloui, 2011). Consequently, the skewed *t* distribution offers an attractive alternative for discussing hedging effectiveness.

Financial asset returns generally feature volatility clustering, and the univariate generalized autoregressive conditional heteroscedasticity (GARCH) model is often used to capture such time-varying volatility (Engle, 1982; Bollerslev, 1986; Baillie and Myers, 1991). However, this model cannot capture the impact of any asymmetry in the volatility of asset returns. Therefore, Glosten *et al.* (1993) proposed the univariate threshold-GARCH (TARCH) model to compensate for this deficiency. Some studies have argued that the univariate TARCH model's ability to capture asymmetric volatility makes it a better tool for hedging against risk (Pochon and Teïletche, 2007; Mokni *et al.*, 2009). However, a hedged portfolio's returns are often correlated and mutually influence the asymmetry in volatility effect, and the univariate TARCH model cannot capture this cross-market asymmetry in volatility of asset returns. Some studies have used the multivariate asymmetric diagonal VECH[1] (ADVECH) model to capture both the asymmetry in volatility and the cross-market asymmetry in volatility of asset returns (de Goeij and Marquering, 2004; Cotter and Hanly, 2012). Chuang *et al.* (2012) proposed a combination between the ADVECH model and the vector error correction model (which is used to analyse how variables respond to deviations from the long-term equilibrium); they termed this model the

[1] VECH denotes the column stacking operator of the lower portion of a matrix.

multivariate VEC–ADVECH model. The VEC–ADVECH model can simultaneously reveal both the movement of the variables in response to deviations from the equilibrium that occurred in the previous period and the asymmetry in volatility and cross-market asymmetry in volatility the covariance matrix of asset returns in the portfolio.

The level effect describes the phenomenon whereby volatility can change in accordance with asset returns. Brenner *et al.* (1996) added the level effect to the GARCH model to capture volatility clustering and the level effect on volatility. They proposed the univariate level GARCH (GARCH–L) model, and found it to have superior forecasting ability compared to the regular univariate GARCH model. However, the level effect can often be observed in the covariance of asset returns. As such, Christiansen (2005) proposed the multivariate GARCH–L model and found that its forecasting ability outperformed the multivariate GARCH model. Additionally, de Goeij and Marquering (2009) expanded the multivariate ADVECH model into the multivariate level ADVECH (ADVECH–L) model that can capture both the level effect and the asymmetric effects on volatility in the covariance matrix of asset returns.

This study has two purposes: first, it proposes the EUM–VaR model for the analysis of both short and long hedged portfolios. Second, with this model, this study investigates the hedging effectiveness of short and long hedged portfolios constructed with multivariate GARCH-type models that feature level effects and multivariate normal distributions, t distributions and skewed t distributions for stock indexes and their corresponding futures in the Greater China Region (Hang Seng, Shanghai A Share and Taiwan).

The first contribution of this study is to risk-optimization theory through the development of a model that can maximize the expected utility of short and long hedged portfolios subject to VaR constraints, that is, the EUM–VaR model. The second contribution of this study is the investigation of the hedging effectiveness of short and long hedged portfolios from multivariate GARCH-type models with level effects and different multivariate distributions for stock indexes and their corresponding futures in the Greater China Region.

The results of this study show that, given identical levels of risk aversion and confidence, the portfolios constructed with the multivariate ADVECH–L model with a skewed t distribution best captured the level effects, asymmetry in volatility and cross-market asymmetry in volatility; they were consequently the most effectively hedged portfolios among those models included in this study. Additionally, the hedging effectiveness of the short and long hedged portfolios concluded consistently. It was further found that multivariate asymmetry in both volatility and distribution should simultaneously be used to construct a hedged portfolio.

The rest of this study is organized as follows: Section II describes the data, the multivariate VEC–ADVECH–L model, the EUM–VaR model and the test for hedging effectiveness. Section III then discusses the empirical results, and Section IV provides this study's conclusions and suggestions for future research.

II. Data and Methodology

Data

The sample period covers 16 April 2010 to 31 October 2013, with 925 observations extracted from the Datastream database. The data set includes the Hang Seng stock index and futures, the Shanghai A Share stock index and futures and the Taiwan stock index and futures.[2] Daily returns on the stock indices and nearby futures were calculated by taking first difference in and the natural logarithm of the daily closing price and multiplying that figure by 100.

Based on the rolling-window framework, this study first uses the ordered pairs of the stock indices and their futures between the 1st and the pth date to estimate the parameters of the researched multivariate GARCH-type model. Then, it substitutes the estimated values of the expected returns vector and covariance matrix for the $p+1$th date into the EUM–VaR model, and obtains the portfolio's optimal hedge

[2] In 1993, the World Bank and International Monetary Fund officially recognized Taiwan, Hong Kong and China as a single economic unit. From 2012 to October 2013, the Hang Seng futures market had a total of 420 931 145 transactions, and thus ranked second among the Asian futures markets, trailing only to Korea with 2 656 282 348 transactions. Meanwhile, the Taiwan futures market ranked third with a trading volume of 309 957 150 transactions and the Chinese futures market ranked fourth with 298 611 136 transactions.

ratio for the $p+1$th date. Next, the window is moved one step ahead and the stock index and futures ordered pairs between the 2nd and $p+1$th date are used to estimate the parameters of the researched multivariate GARCH-type model. This process is repeated until the portfolio's optimal hedge ratio for the last date is obtained.

Multivariate VEC–ADVECH–L model

The multivariate VEC–ADVECH–L model is specified as

$$r_{i,t} = a_i + b_i r_{i,t-1} + c_i\left(ln P_{1,t-1} - \kappa - \delta ln P_{2,t-1}\right) + d_j r_{j,t-1} + \varepsilon_{i,t}$$
$$i,j = 1,2, i \neq j \quad (1)$$

$$\begin{aligned}\sigma_{ij,t} = {} & \left|r_{i,t-1} r_{j,t-1}\right|^{\gamma_{ij}} \times (\tau_{ij} + \alpha_{1ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} \\ & + \alpha_{2ij} I_{\varepsilon_{i,t-1}}\varepsilon_{i,t-1} I_{\varepsilon_{j,t-1}}\varepsilon_{j,t-1} \\ & + \alpha_{3ij}(1 - I_{\varepsilon_{i,t-1}})\varepsilon_{i,t-1} I_{\varepsilon_{j,t-1}}\varepsilon_{j,t-1} \\ & + \alpha_{4ij} I_{\varepsilon_{i,t-1}}\varepsilon_{i,t-1}(1 - I_{\varepsilon_{j,t-1}})\varepsilon_{j,t-1} \\ & + \beta_{ij}\sigma_{ij,t-1}), \quad i,j = 1,2\end{aligned} \quad (2)$$

$$\rho_{ij,t} = exp\left(q_{ij,t}\right) / \left(1 + exp\left(q_{ij,t}\right)\right), \; i,j = 1,2, \; i \neq j \quad (3)$$

$$\begin{aligned}q_{ij,t} = {} & \varpi_0 + \varpi_1 \rho_{ij,t-1} \\ & + \varpi_2\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} \Big/ \sqrt{\sigma^2_{ii,t-1}\sigma^2_{jj,t-1}}\right), \quad (4) \\ i,j = {} & 1,2, \; i \neq j\end{aligned}$$

where $i = 1$ is the stock index and $j = 2$ is the corresponding index futures. Equation 1 represents the asset returns for index i, and $\varepsilon_t = \left[\varepsilon_{i,t} \; \varepsilon_{j,t}\right]'$ follows a multivariate normal distribution, multivariate t distribution or multivariate skewed t distribution. The speed of adjustment toward equilibrium is determined by the magnitude of c_i. Equation 2 represents the conditional covariance of returns between assets i and j at time t while γ_{ij} is used to capture the level effect. Consequently, if γ_{ij} is not equal to zero, then the conditional covariance will be determined by returns and news shocks. The sensitivity of the conditional covariance to returns increases with γ_{ij}. As such, if γ_{ij} does equal zero, then the conditional covariance will only be determined by news shocks (this is the same VEC–ADVECH model used by Chuang *et al.,* 2012). Equations 3 and 4 are based on the dynamic conditional correlation put forth by Tsay (2009). Table 1 compares the model specifications and parameter restrictions.

Since the log likelihood function is a nonlinear function of the parameters, the maximum likelihood parameter estimates of an alternative multivariate volatility model are obtained using the Berndt–Hall–Hall–Hausman (BHHH) algorithm (Berndt *et al.*, 1974).

EUM–VaR model

This study defines a short hedged portfolio as one that is long in the spot and short in the futures. Conversely, a long hedged portfolio is short in the spot and long in the futures. Let $r_{s,t}$ and $r_{f,t}$ denote the returns on the spot and the futures at time t, respectively, and let β_t represent the portfolio's hedge ratios from the EUM–VaR model. Given a confidence level of $1-\alpha$, the EUM–VaR model for the short hedged portfolio can be written as

$$\underset{\beta_t}{\text{Max}}\, E\left(r_{p,t}\right) - v\sigma^2_{p,t} \Big/ 2 \quad (5)$$

$$\text{s.t. } VaR^{short}_{p,t} \le E\left(r_{p,t}\right) + \delta_{1-\alpha}\sigma_{p,t} \quad (6)$$

$$0 \le \beta_t \le 1 \quad (7)$$

while that for the long hedged portfolio can be given as

$$\underset{\beta_t}{\text{Max}}\, E\left(r_{p,t}\right) - v\sigma^2_{p,t} \Big/ 2 \quad (8)$$

$$\text{s.t. } VaR^{long}_{p,t} \ge E\left(r_{p,t}\right) + \delta_{\alpha}\sigma_{p,t} \quad (9)$$

$$0 \le \beta_t \le 1 \quad (10)$$

where $r_{p,t}$ represents the returns on the hedged portfolio at time t and $E\left(r_{p,t}\right)$ denotes the expected returns. $\sigma^2_{p,t}$ represents the variance of the hedged

Table 1. Comparison of model specifications and parameter restrictions

	Model	Distribution	γ	α_1	α_2, α_3 and α_4
Non-level effect model	VEC-DVECH	Normal	0	–	0
	VEC-ADVECH	Normal	0	–	–
	VEC-DVECH	*t*	0	–	0
	VEC-ADVECH	*t*	0	–	–
	VEC-DVECH	Skewed *t*	0	–	0
	VEC-ADVECH	Skewed *t*	0	–	–
Level effect model	VEC-DVECH-L	Normal	–	–	0
	VEC-ADVECH-L	Normal	–	–	–
	VEC-DVECH-L	*t*	–	–	0
	VEC-ADVECH-L	*t*	–	–	–
	VEC-DVECH-L	Skewed *t*	–	–	0
	VEC-ADVECH-L	Skewed *t*	–	–	–

Notes: 1. VEC-DVECH is a multivariate DVECH model with a VEC term. VEC-ADVECH represents a multivariate asymmetry DVECH model with a VEC term. VEC-DVECH-L is a multivariate DVECH-L model with level effect. VEC-ADVECH-L denotes a multivariate ADVECH-L model with level effect.
2.'–'denotes there is unrestrained.

portfolio's returns at time t. Additionally, $VaR_{p,t}^{short}$ and $VaR_{p,t}^{long}$ are the values-at-risk for the short and long hedged portfolios at time t, respectively. δ_α is the αth percentile of the standard normal distribution, t distribution or skewed t distribution (depending on the test). This study sets α at either 1% or 5%. v is the decision-maker's degree of risk aversion, and it is set at 1, 10 or 100. This method is based on the work of Yang and Lai (2009) who presented the concept that $v = 1$ represents a risk-lover and $v = 100$ represents a risk-averter.

Test for hedging effectiveness

Hedging effectiveness (HE) is defined as the variance of the unhedged asset returns (σ_u^2) compared to the variance of the hedged portfolio from a multivariate GARCH-type model (σ_h^2), that is,

$$HE = \left(\sigma_u^2 - \sigma_h^2\right)/\sigma_u^2 \tag{11}$$

The greater HE is, the higher the hedging effectiveness of the hedged portfolio relative to the unhedged asset returns. The F-test statistic is used to test the hedging effectiveness, and the null and alternative hypotheses are

$$H_0 : \left(\sigma_h^2/\sigma_u^2\right) \geq 1 \text{ versus } H_1 : \left(\sigma_h^2/\sigma_u^2\right) < 1 \tag{12}$$

Given the α significance level, the null hypothesis will be rejected when $\left(\sigma_h^2/\sigma_u^2\right) < F_{n_h,n_u,\alpha}$, where $F_{n_h,n_u,\alpha}$ represents the 100αth quantile of the F distribution with n_h degrees of freedom for the variance of the hedged portfolio and n_u degrees of freedom for the variance of the unhedged asset returns.

III. Empirical Results

Table 2 lists the summary statistics for the data set. According to the Jarque–Bera test, the stock indices and futures in the Greater China Region do not appear to be normally distributed (at the 5% significance level). Tables 3 and 4 show the average hedge ratios for the long and short hedged portfolios based on the EUM–VaR model, respectively. The short hedged ratios range from 0.4712 to 0.9282 and the long hedged ratios range from 0.4854 to 0.9292. Meanwhile, of all the models used to design hedging portfolios, the VEC–ADVECH–L model with a skewed t distribution showed the largest average hedge ratios for both the short and long hedged portfolios. The hedge ratios indicate that futures effectively hedge against stock indices in the Greater China Region.

Based on the EUM–VaR model, Tables 5 and 6 illustrate the hedging effectiveness of the short and long hedged portfolios, respectively. At the 5% significance level, the hedging effectiveness values of

Table 2. Summary statistics

	Hang Seng		Shanghai A-share		Taiwan	
Statistic	Stock index	Futures	Stock index	Futures	Stock index	Futures
Mean	0.0078	0.0064	−0.0595	−0.0604	−0.0162	−0.0166
Standard deviation	1.2357	1.2022	1.2914	1.4907	1.2373	1.1529
Skewness	−0.1287	−0.2731	−0.5628	−0.4098	−0.5946	−0.6924
Exceess kurtosis	4.7954**	6.6746**	4.9611**	6.3047**	5.7176**	5.4060**
Jarque–Bera	126.640**	286.893**	85.427**	193.696**	147.022**	128.765**
LB *Q* (12)	7.0070	12.9270	12.7140	13.4450	13.8690	18.209
LB *Q*2(12)	219.751**	260.812**	10.1500	12.9650	79.8490**	112.7060**
SBT	6.2076**	2.8110	0.0007	0.4178	3.1010	11.6943**
	(1.9375)	(2.1540)	(2.0597)	(2.3814)	(2.2018)	(2.0584)
NSBT	3.7275*	7.9544**	0.0359	0.1407	24.7041**	39.6136**
	(1.9405)	(2.1480)	(1.9932)	(2.2437)	(2.1600)	(1.9678)
PSBT	0.4189	0.0001	0.0977	0.0075	3.2939	2.3483
	(1.9439)	(2.1572)	(1.9951)	(2.2438)	(2.1849)	(1.9829)
JT	197.8625*	169.5046*	180.7382*	146.7306*	178.8943*	103.6636*

Notes: 1. ** (*) denotes statistical significance at the 1% (5%) significant level.
2. LB Q (12) represents Ljung-Box Q test statistics of lag 12; the critical value is 26.217 (21.0261) at the 1% (5%) significance level.
3. LB Q2 (12) refers to Ljung-Box Q test statistics of lag 12 for squared series; the critical value is 26.217 (21.0261) at the 1% (5%) significance level.
4. SBT, NSBT, PSBT and JT, respectively, denote the sign bias test (SBT), negative size bias test (NSBT), positive size bias test (PSBT) and joint test (JT) proposed by Engle and Ng (1993). JT is a chi-square distribution with three degrees of freedom. The critical value is 7.82 at the 5% significance level.
5. The figures in brackets denote standard error.

Table 3. Average hedge ratios of short hedged portfolios from EUM–VaR models

		99% confidence level			95% confidence level		
Model	Hedged portfolio	$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
Panel A: Normal distribution							
VEC-DVECH	HS	0.5029	0.5034	0.5035	0.5037	0.5041	0.5042
		(0.2664)	(0.2361)	(0.2315)	(0.2301)	(0.2290)	(0.2284)
	SA	0.4712	0.4738	0.4782	0.4791	0.4814	0.4831
		(0.2302)	(0.2300)	(0.2299)	(0.2295)	(0.2293)	(0.2292)
	TW	0.7825	0.7889	0.7896	0.7897	0.7908	0.7913
		(0.2379)	(0.2352)	(0.2309)	(0.2250)	(0.2168)	(0.2106)
VEC-ADVECH	HS	0.8850	0.8852	0.8854	0.8856	0.8860	0.8875
		(0.1356)	(0.1351)	(0.1349)	(0.1346)	(0.1340)	(0.1337)
	SA	0.6830	0.6838	0.6847	0.6858	0.6878	0.6937
		(0.1691)	(0.1690)	(0.1689)	(0.1686)	(0.1679)	(0.1668)
	TW	0.8293	0.8298	0.8302	0.8305	0.8318	0.8326
		(0.1602)	(0.1600)	(0.1597)	(0.1596)	(0.1594)	(0.1591)
VEC-DVECH-L	HS	0.6481	0.6578	0.7399	0.7432	0.7556	0.7558
		(0.1568)	(0.1567)	(0.1549)	(0.1525)	(0.1518)	(0.1513)
	SA	0.5460	0.5462	0.5465	0.5466	0.5470	0.5473
		(0.1983)	(0.1982)	(0.1965)	(0.1960)	(0.1954)	(0.1951)
	TW	0.8115	0.8117	0.8120	0.8135	0.8138	0.8142
		(0.1766)	(0.1755)	(0.1747)	(0.1741)	(0.1740)	(0.1737)

(*continued*)

Table 3. Continued

Model	Hedged portfolio	99% confidence level			95% confidence level		
		$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
VEC-ADVECH-L	HS	0.9132	0.9135	0.9138	0.9140	0.9146	0.9152
		(0.1202)	(0.1197)	(0.1196)	(0.1195)	(0.1194)	(0.1193)
	SA	0.8066	0.8075	0.8102	0.8109	0.8115	0.8126
		(0.1410)	(0.1405)	(0.1400)	(0.1396)	(0.1394)	(0.1391)
	TW	0.8638	0.8651	0.8667	0.8668	0.8705	0.8710
		(0.1466)	(0.1459)	(0.1456)	(0.1449)	(0.1448)	(0.1442)
Panel B: *t* distribution							
VEC-DVECH	HS	0.5864	0.5865	0.5935	0.5938	0.5940	0.5943
		(0.2086)	(0.2072)	(0.2032)	(0.1912)	(0.1911)	(0.1910)
	SA	0.5117	0.5124	0.5142	0.5152	0.5173	0.5192
		(0.2255)	(0.2246)	(0.2242)	(0.2240)	(0.2240)	(0.2239)
	TW	0.7959	0.7963	0.7974	0.7986	0.7990	0.7995
		(0.1959)	(0.1941)	(0.1939)	(0.1916)	(0.1892)	(0.1890)
VEC-ADVECH	HS	0.8982	0.8986	0.8989	0.9006	0.9022	0.9024
		(0.1313)	(0.1299)	(0.1293)	(0.1275)	(0.1262)	(0.1251)
	SA	0.7273	0.7280	0.7326	0.7338	0.7681	0.7699
		(0.1585)	(0.1569)	(0.1556)	(0.1548)	(0.1537)	(0.1519)
	TW	0.8389	0.8394	0.8395	0.8396	0.8420	0.8423
		(0.1575)	(0.1571)	(0.1570)	(0.1566)	(0.1565)	(0.1561)
VEC-DVECH-L	HS	0.8052	0.8069	0.8105	0.8143	0.8160	0.8215
		(0.1479)	(0.1476)	(0.1474)	(0.1470)	(0.1463)	(0.1461)
	SA	0.6239	0.6248	0.6300	0.6340	0.6363	0.6382
		(0.1885)	(0.1884)	(0.1851)	(0.1840)	(0.1812)	(0.1810)
	TW	0.8171	0.8172	0.8175	0.8177	0.8180	0.8184
		(0.1714)	(0.1711)	(0.1706)	(0.1702)	(0.1693)	(0.1680)
VEC-ADVECH-L	HS	0.9185	0.9198	0.9199	0.9203	0.9220	0.9222
		(0.1178)	(0.1176)	(0.1172)	(0.1169)	(0.1167)	(0.1166)
	SA	0.8155	0.8165	0.8170	0.8172	0.8176	0.8179
		(0.1355)	(0.1353)	(0.1350)	(0.1348)	(0.1342)	(0.1340)
	TW	0.8762	0.8781	0.8784	0.8808	0.8817	0.8830
		(0.1420)	(0.1419)	(0.1418)	(0.1413)	(0.1412)	(0.1408)
Panel C: Skewed *t* distribution							
VEC-DVECH	HS	0.6029	0.6037	0.6080	0.6086	0.6090	0.6114
		(0.1693)	(0.1688)	(0.1650)	(0.1643)	(0.1628)	(0.1595)
	SA	0.5305	0.5319	0.5332	0.5355	0.5370	0.5380
		(0.2196)	(0.2195)	(0.2195)	(0.2195)	(0.2150)	(0.2146)
	TW	0.8036	0.8040	0.8047	0.8050	0.8062	0.8066
		(0.1862)	(0.1860)	(0.1845)	(0.1830)	(0.1815)	(0.1811)
VEC-ADVECH	HS	0.9077	0.9084	0.9090	0.9091	0.9092	0.9094
		(0.1232)	(0.1228)	(0.1226)	(0.1222)	(0.1217)	(0.1216)
	SA	0.7834	0.7845	0.7877	0.7881	0.7888	0.7914
		(0.1475)	(0.1473)	(0.1466)	(0.1464)	(0.1450)	(0.1444)
	TW	0.8537	0.8548	0.8553	0.8557	0.8561	0.8563
		(0.1521)	(0.1519)	(0.1518)	(0.1516)	(0.1509)	(0.1498)
VEC-DVECH-L	HS	0.8442	0.8492	0.8496	0.8533	0.8563	0.8636
		(0.1419)	(0.1415)	(0.1393)	(0.1391)	(0.1387)	(0.1385)
	SA	0.6677	0.6705	0.6709	0.6711	0.6722	0.6745
		(0.1758)	(0.1758)	(0.1758)	(0.1757)	(0.1746)	(0.1741)
	TW	0.8229	0.8230	0.8231	0.8232	0.8235	0.8239
		(0.1654)	(0.1649)	(0.1644)	(0.1643)	(0.1638)	(0.1629)

(*continued*)

Table 3. Continued

		99% confidence level			95% confidence level		
Model	Hedged portfolio	$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
VEC-ADVECH-L	HS	0.9264	0.9265	0.9267	0.9267	0.9276	0.9282
		(0.1157)	(0.1154)	(0.1152)	(0.1144)	(0.1142)	(0.1140)
	SA	0.8219	0.8225	0.8231	0.8234	0.8236	0.8238
		(0.1302)	(0.1287)	(0.1273)	(0.1272)	(0.1271)	(0.1266)
	TW	0.8917	0.8917	0.8928	0.8939	0.8945	0.8956
		(0.1375)	(0.1360)	(0.1341)	(0.1330)	(0.1322)	(0.1318)

Notes: 1. VEC-DVECH is a multivariate DVECH model with a VEC term. VEC-ADVECH represents a multivariate asymmetry DVECH model with a VEC term. VEC-DVECH-L is a multivariate DVECH-L model with level effect. VEC-ADVECH-L denotes a multivariate ADVECH-L model with level effect.
2. HS, SA and TW denote the Hang Seng, Shanghai A-share and Taiwan stock index and futures portfolios, respectively.
3. v indicates the degree of risk aversion.
4. The figures in brackets denote standard deviations.

Table 4. Average hedge ratios of long hedged portfolios from EUM–VaR models

		99% confidence level			95% confidence level		
Model	Hedged portfolio	$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
Panel A: Normal distribution							
VEC-DVECH	HS	0.5121	0.5125	0.5126	0.5187	0.5191	0.5192
		(0.2198)	(0.2152)	(0.2131)	(0.2121)	(0.2100)	(0.2097)
	SA	0.4854	0.4880	0.4899	0.4943	0.4964	0.4981
		(0.2285)	(0.2282)	(0.2269)	(0.2268)	(0.2257)	(0.2256)
	TW	0.7923	0.7938	0.7949	0.7956	0.7956	0.7958
		(0.2101)	(0.2070)	(0.2046)	(0.2035)	(0.1991)	(0.1969)
VEC-ADVECH	HS	0.8876	0.8893	0.8920	0.8942	0.8944	0.8976
		(0.1331)	(0.1324)	(0.1322)	(0.1321)	(0.1320)	(0.1318)
	SA	0.7107	0.7114	0.7186	0.7196	0.7220	0.7230
		(0.1648)	(0.1645)	(0.1640)	(0.1637)	(0.1635)	(0.1600)
	TW	0.8332	0.8333	0.8343	0.8350	0.8364	0.8365
		(0.1587)	(0.1586)	(0.1583)	(0.1578)	(0.1576)	(0.1575)
VEC-DVECH-L	HS	0.7633	0.7764	0.7790	0.7885	0.7890	0.7993
		(0.1513)	(0.1509)	(0.1500)	(0.1499)	(0.1489)	(0.1482)
	SA	0.5511	0.5515	0.5518	0.5538	0.5543	0.5544
		(0.1944)	(0.1938)	(0.1914)	(0.1907)	(0.1893)	(0.1890)
	TW	0.8155	0.8155	0.8160	0.8161	0.8165	0.8167
		(0.1735)	(0.1728)	(0.1725)	(0.1722)	(0.1717)	(0.1716)
VEC-ADVECH-L	HS	0.9165	0.9166	0.9169	0.9172	0.9174	0.9180
		(0.1189)	(0.1188)	(0.1188)	(0.1188)	(0.1181)	(0.1179)
	SA	0.8127	0.8135	0.8141	0.8149	0.8151	0.8152
		(0.1386)	()0.1378	(0.1374)	(0.1363)	(0.1361)	(0.1356)
	TW	0.8713	0.8721	0.8724	0.8728	0.8736	0.8750
		(0.1438)	(0.1426)	(0.1426)	(0.1422)	(0.1422)	(0.1421)
Panel B: *t* distribution							
VEC-DVECH	HS	0.5946	0.5987	0.5996	0.6001	0.6021	0.6022
		(0.1879)	(0.1853)	(0.1820)	(0.1813)	(0.1787)	(0.1741)
	SA	0.5201	0.5212	0.5234	0.5252	0.5274	0.5294
		(0.2237)	(0.2233)	(0.2229)	(0.2218)	(0.2218)	(0.2218)
	TW	0.8002	0.8007	0.8021	0.8022	0.8032	0.8035
		(0.1888)	(0.1883)	(0.1881)	(0.1878)	(0.1874)	(0.1872)

(*continued*)

Table 4. Continued

Model	Hedged portfolio	99% confidence level			95% confidence level		
		$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
VEC-ADVECH	HS	0.9027	0.9028	0.9032	0.9044	0.9071	0.9072
		(0.1247)	(0.1246)	(0.1243)	(0.1241)	(0.1240)	(0.1233)
	SA	0.7708	0.7737	0.7796	0.7800	0.7801	0.7832
		(0.1509)	(0.1506)	(0.1496)	(0.1487)	(0.1477)	(0.1474)
	TW	0.8425	0.8444	0.8455	0.8486	0.8496	0.8523
		(0.1556)	(0.1554)	(0.1548)	(0.1546)	(0.1536)	(0.1529)
VEC-DVECH-L	HS	0.8253	0.8270	0.8325	0.8377	0.8408	0.8434
		(0.1448)	(0.1447)	(0.1445)	(0.1438)	(0.1423)	(0.1421)
	SA	0.6385	0.6475	0.6493	0.6504	0.6602	0.6645
		(0.1809)	(0.1793)	(0.1767)	(0.1761)	(0.1761)	(0.1761)
	TW	0.8195	0.8204	0.8206	0.8209	0.8215	0.8218
		(0.1675)	(0.1670)	(0.1667)	(0.1666)	(0.1657)	(0.1655)
VEC-ADVECH-L	HS	0.9225	0.9247	0.9247	0.9258	0.9260	0.9263
		(0.1164)	(0.1163)	(0.1162)	(0.1161)	(0.1159)	(0.1158)
	SA	0.8183	0.8186	0.8191	0.8199	0.8204	0.8206
		(0.1334)	(0.1330)	(0.1324)	(0.1315)	(0.1312)	(0.1305)
	TW	0.8836	0.8836	0.8840	0.8848	0.8854	0.8916
		(0.1407)	(0.1403)	(0.1393)	(0.1384)	(0.1380)	(0.1379)
Panel C: Skewed *t* distribution							
VEC-DVECH	HS	0.6117	0.6129	0.6137	0.6148	0.6323	0.6411
		(0.1593)	(0.1591)	(0.1586)	(0.1585)	(0.1580)	(0.1575)
	SA	0.5386	0.5395	0.5406	0.5415	0.5432	0.5451
		(0.2118)	(0.2083)	(0.2057)	(0.2048)	(0.2015)	(0.2001)
	TW	0.8073	0.8078	0.8104	0.8109	0.8110	0.8112
		(0.1792)	(0.1792)	(0.1789)	(0.1789)	(0.1787)	(0.1782)
VEC-ADVECH	HS	0.9105	0.9110	0.9111	0.9115	0.9119	0.9122
		(0.1215)	(0.1214)	(0.1213)	(0.1212)	(0.1211)	(0.1203)
	SA	0.7981	0.7993	0.8000	0.8010	0.8035	0.8051
		(0.1442)	(0.1438)	(0.1435)	(0.1432)	(0.1423)	(0.1411)
	TW	0.8565	0.8572	0.8587	0.8605	0.8617	0.8625
		(0.1489)	(0.1488)	(0.1487)	(0.1486)	(0.1482)	(0.1470)
VEC-DVECH-L	HS	0.8654	0.8739	0.8745	0.8749	0.8792	0.8797
		(0.1383)	(0.1378)	(0.1368)	(0.1365)	(0.1363)	(0.1360)
	SA	0.6762	0.6767	0.6771	0.6777	0.6788	0.6790
		(0.1740)	(0.1724)	(0.1718)	(0.1708)	(0.1694)	(0.1691)
	TW	0.8259	0.8271	0.8278	0.8280	0.8288	0.8291
		(0.1629)	(0.1621)	(0.1612)	(0.1611)	(0.1609)	(0.1603)
VEC-ADVECH-L	HS	0.9283	0.9285	0.9286	0.9287	0.9290	0.9292
		(0.1138)	(0.1136)	(0.1128)	(0.1122)	(0.1121)	(0.1120)
	SA	0.8240	0.8245	0.8251	0.8253	0.8254	0.8261
		(0.1259)	(0.1256)	(0.1253)	(0.1250)	(0.1246)	(0.1234)
	TW	0.8985	0.8990	0.8995	0.9008	0.9032	0.9033
		(0.1317)	(0.1316)	(0.1314)	(0.1297)	(0.1289)	(0.1264)

Notes: 1. VEC-DVECH is a multivariate DVECH model with a VEC term. VEC-ADVECH represents a multivariate asymmetry DVECH model with a VEC term. VEC-DVECH-L is a multivariate DVECH-L model with level effect. VEC-ADVECH-L denotes a multivariate ADVECH-L model with level effect.
2. HS, SA and TW denote the Hang Seng, Shanghai A-share and Taiwan stock index and futures portfolios, respectively.
3. v indicates the degree of risk aversion.
4. The figures in brackets denote standard deviations.

Table 5. Test for the hedging effectiveness of short hedged portfolios from EUM–VaR models

		99% confidence level			95% confidence level		
Model	Hedged portfolio	$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
Panel A: Normal distribution							
VEC-DVECH	HS	0.7698**	0.7757**	0.7932**	0.7934**	0.7961**	0.7963**
	SA	0.7397**	0.7407**	0.7411**	0.7484**	0.7491**	0.7492**
	TW	0.6134**	0.6141**	0.6174**	0.6236**	0.6243**	0.6252**
VEC-ADVECH	HS	0.9007**	0.9015**	0.9021**	0.9039**	0.9050**	0.9054**
	SA	0.9092**	0.9102**	0.9142**	0.9153**	0.9167**	0.9185**
	TW	0.7479**	0.7487**	0.7513**	0.7519**	0.7557**	0.7594**
VEC-DVECH-L	HS	0.8528**	0.8605**	0.8607**	0.8609**	0.8615**	0.8618**
	SA	0.8630**	0.8638**	0.8656**	0.8665**	0.8671**	0.8717**
	TW	0.7050**	0.7061**	0.7068**	0.7075**	0.7086**	0.7090**
VEC-ADVECH-L	HS	0.9336**	0.9337**	0.9346**	0.9347**	0.9354**	0.9356**
	SA	0.9394**	0.9396**	0.9400**	0.9410**	0.9414**	0.9429**
	TW	0.8188**	0.8190**	0.8193**	0.8205**	0.8238**	0.8242**
Panel B: *t* distribution							
VEC-DVECH	HS	0.8003**	0.8018**	0.8021**	0.8029**	0.8035**	0.8054**
	SA	0.7661**	0.7668**	0.7678**	0.7685**	0.7692**	0.7697**
	TW	0.6443**	0.6454**	0.6460**	0.6464**	0.6470**	0.6488**
VEC-ADVECH	HS	0.9184**	0.9190**	0.9194**	0.9195**	0.9206**	0.9207**
	SA	0.9259**	0.9260**	0.9261**	0.9263**	0.9267**	0.9270**
	TW	0.7678**	0.7696**	0.7709**	0.7711**	0.7724**	0.7739**
VEC-DVECH-L	HS	0.8725**	0.8725**	0.8727**	0.8729**	0.8792**	0.8816**
	SA	0.8969**	0.8984**	0.8987**	0.8990**	0.8995**	0.8999**
	TW	0.7191**	0.7192**	0.7207**	0.7220**	0.7231**	0.7243**
VEC-ADVECH-L	HS	0.9385**	0.9391**	0.9394**	0.9395**	0.9397**	0.9401**
	SA	0.9459**	0.9471**	0.9473**	0.9477**	0.9500**	0.9502**
	TW	0.8311**	0.8315**	0.8320**	0.8325**	0.8333**	0.8340**
Panel C: Skewed *t* distribution							
VEC-DVECH	HS	0.8376**	0.8387**	0.8388**	0.8391**	0.8392**	0.8393**
	SA	0.7740**	0.7743**	0.7756**	0.7766**	0.7778**	0.7794**
	TW	0.6575**	0.6595**	0.6610**	0.6619**	0.6637**	0.6651**
VEC-ADVECH	HS	0.9236**	0.9246**	0.9246**	0.9280**	0.9291**	0.9301**
	SA	0.9322**	0.9335**	0.9346**	0.9348**	0.9366**	0.9369**
	TW	0.7825**	0.7846**	0.7878**	0.7890**	0.7898**	0.7915**
VEC-DVECH-L	HS	0.8871**	0.8886**	0.8887**	0.8890**	0.8892**	0.8916**
	SA	0.9032**	0.9034**	0.9036**	0.9040**	0.9045**	0.9047**
	TW	0.7316**	0.7330**	0.7342**	0.7347**	0.7366**	0.7383**
VEC-ADVECH-L	HS	0.9439**	0.9441**	0.9442**	0.9443**	0.9444**	0.9446**
	SA	0.9526**	0.9528**	0.9529**	0.9531**	0.9539**	0.9542**
	TW	0.8382**	0.8383**	0.8435**	0.8444**	0.8447**	0.8451**

Notes: 1. VEC-DVECH is a multivariate DVECH model with a VEC term. VEC-ADVECH represents a multivariate asymmetry DVECH model with a VEC term. VEC-DVECH-L is a multivariate DVECH-L model with level effect. VEC-ADVECH-L denotes a multivariate ADVECH-L model with level effect.
2. HS, SA and TW denote the Hang Seng, Shanghai A-share and Taiwan stock index and futures portfolios, respectively.
3. v indicates the degree of risk aversion.
4. ** denotes statistical significance at the 1% significant level.

both the short and long hedged portfolios were significantly below 1; that is, the hedging effectiveness of these portfolios was better than that of the unhedged portfolios. Therefore, as either the multivariate GARCH-type models or the use of asymmetric distributions to represent the asset returns could capture the dynamic correlations, the portfolios from the EUM–VaR model were effective at in hedging.

If asset returns follow a multivariate normal distribution and a multivariate VEC–ADVECH model

Table 6. Test for the hedging effectiveness of long hedged portfolios from EUM–VaR models

Model	Hedged portfolio	99% confidence level			95% confidence level		
		$v = 1$	$v = 10$	$v = 100$	$v = 1$	$v = 10$	$v = 100$
Panel A: Normal distribution							
VEC-DVECH	HS	0.7967**	0.7969**	0.7982**	0.7987**	0.7992**	0.7997**
	SA	0.7636**	0.7638**	0.7639**	0.7642**	0.7643**	0.7654**
	TW	0.6284**	0.6286**	0.6324**	0.6348**	0.6398**	0.6405**
VEC-ADVECH	HS	0.9106**	0.9109**	0.9146**	0.9148**	0.9149**	0.9178**
	SA	0.9228**	0.9232**	0.9237**	0.9237**	0.9254**	0.9256**
	TW	0.7601**	0.7609**	0.7611**	0.7618**	0.7627**	0.7673**
VEC-DVECH-L	HS	0.8629**	0.8642**	0.8646**	0.8651**	0.8693**	0.8703**
	SA	0.8739**	0.8741**	0.8781**	0.8902**	0.8914**	0.8942**
	TW	0.7101**	0.7115**	0.7128**	0.7138**	0.7158**	0.7163**
VEC-ADVECH-L	HS	0.9360**	0.9368**	0.9373**	0.9378**	0.9379**	0.9381**
	SA	0.9429**	0.9430**	0.9436**	0.9441**	0.9441**	0.9443**
	TW	0.8246**	0.8255**	0.8262**	0.8267**	0.8269**	0.8273**
Panel B: *t* distribution							
VEC-DVECH	HS	0.8218**	0.8274**	0.8280**	0.8339**	0.8343**	0.8345**
	SA	0.7700**	0.7701**	0.7708**	0.7717**	0.7724**	0.7730**
	TW	0.6509**	0.6527**	0.6540**	0.6543**	0.6547**	0.6559**
VEC-ADVECH	HS	0.9209**	0.9210**	0.9223**	0.9229**	0.9234**	0.9235**
	SA	0.9271**	0.9272**	0.9276**	0.9280**	0.9281**	0.9306**
	TW	0.7742**	0.7746**	0.7761**	0.7781**	0.7793**	0.7822**
VEC-DVECH-L	HS	0.8817**	0.8818**	0.8827**	0.8829**	0.8839**	0.8856**
	SA	0.9000**	0.9011**	0.9023**	0.9025**	0.9030**	0.9032**
	TW	0.7248**	0.7265**	0.7277**	0.7286**	0.7290**	0.7297**
VEC-ADVECH-L	HS	0.9409**	0.9416**	0.9426**	0.9430**	0.9434**	0.9436**
	SA	0.9504**	0.9505**	0.9507**	0.9516**	0.9520**	0.9523**
	TW	0.8352**	0.8354**	0.8357**	0.8363**	0.8369**	0.8377**
Panel C: Skewed *t* distribution							
VEC-DVECH	HS	0.8421**	0.8439**	0.8468**	0.8478**	0.8495**	0.8518**
	SA	0.7800**	0.7814**	0.7827**	0.7841**	0.7843**	0.7851**
	TW	0.6664**	0.6677**	0.6699**	0.6713**	0.6720**	0.6733**
VEC-ADVECH	HS	0.9313**	0.9316**	0.9320**	0.9324**	0.9330**	0.9331**
	SA	0.9372**	0.9375**	0.9378**	0.9380**	0.9389**	0.9391**
	TW	0.7918**	0.7935**	0.7949**	0.7962**	0.7970**	0.7976**
VEC-DVECH-L	HS	0.8916**	0.8938**	0.8947**	0.8988**	0.9000**	0.9004**
	SA	0.9049**	0.9052**	0.9054**	0.9055**	0.9059**	0.9066**
	TW	0.7388**	0.7398**	0.7409**	0.7416**	0.7434**	0.7439**
VEC-ADVECH-L	HS	0.9448**	0.9449**	0.9452**	0.9455**	0.9457**	0.9459**
	SA	0.9548**	0.9552**	0.9562**	0.9570**	0.9576**	0.9584**
	TW	0.8455**	0.8458**	0.8466**	0.8473**	0.8479**	0.8484**

Notes: 1. VEC-DVECH is a multivariate DVECH model with a VEC term. VEC-ADVECH represents a multivariate asymmetry DVECH model with a VEC term. VEC-DVECH-L is a multivariate DVECH-L model with level effect. VEC-ADVECH-L denotes a multivariate ADVECH-L model with level effect.
2. HS, SA and TW denote the Hang Seng, Shanghai A-share and Taiwan stock index and futures portfolios, respectively.
3. v indicates the degree of risk aversion.
4. ** denotes statistical significance at the 1% significant level.

is used, then the least effective short and long hedged portfolios have hedging effectiveness figures equal to 0.6134 and 0.6284, respectively. However, if the asset returns follow the multivariate *t* distribution, then with the worst hedging effectiveness figures for the short and long hedged portfolios are 0.6443 and 0.6509, respectively. Finally, if a multivariate skewed *t* distribution is used, then 0.6575 is the lowest hedging effectiveness among the short hedged portfolios and 0.6664 is the lowest among the long hedged portfolios. All else equal, the hedging effectiveness figures are greatest when the multivariate skewed *t* distribution is applied to the asset returns. Thus, it can be concluded that the multivariate skewed *t* distribution can effectively capture the heavy tails and skewness of the asset returns distribution.

Overall, the hedging effectiveness of the risk-averse investors' portfolios is better than that of the risk-loving investors. When all other factors are held constant, the portfolios from models that include level effects outperform those that do not; this phenomenon may be attributed to the multivariate GARCH-type models with level effects' ability to capture changes in volatility. Additionally, both the long and short hedged portfolios are more effective when multivariate asymmetric GARCH-type models are used than when symmetric ones are used, as they are better able to account for both asymmetry in volatility and cross-market asymmetry in volatility. Furthermore, among all of the models included in this study, the ones that were most effective in hedging were the VEC–ADVECH–L models with multivariate skewed *t* distributions.

IV. Conclusions and Suggestions

It is necessary to account for the dynamic correlation of asset returns in the construction of a hedged portfolio. As such, based on the EUM–VaR model, this study constructed short and long hedged portfolios with multivariate GARCH-type models that featured different distributions, and investigated the hedging effectiveness of both short and long hedged portfolios that included stock indexes and their corresponding futures from the Greater China Region.

The results show that, regardless of the multivariate GARCH-type model used or the asymmetry in the distribution of the asset returns, portfolios can be effectively hedged in either the short or the long hedged portfolios. Since the multivariate VEC–ADVECH–L model with a skewed *t* distribution can simultaneously capture asymmetry in the distribution, level effects and asymmetry in volatility and cross-market asymmetry in volatility, it was the most effective at hedging. As such, investors should utilize this model in the formation of the short and long hedged portfolios. Additionally, the hedging effectiveness of the risk-lover investors was inferior to that of the risk-averter. Moreover, the hedging effectiveness of the short and long hedged portfolios from the multivariate GARCH-type models with level effect was better than that of the multivariate GARCH-type models with non-level effect. Furthermore, since the EUM–VaR model can maximize the trade-off between the risk and return of a hedged portfolio subject to a maximum possible loss at a given confidence level, it should be used to determine the hedge ratios in portfolios and to modify the mean-VaR optimality criterion.

Additionally, the multivariate VEC-ADVECH-L model with the multivariate skewed *t* distribution can simultaneously capture asymmetry in distribution, level effect in volatility, asymmetry in volatility and cross-market asymmetry in volatility of asset returns in a hedged portfolio, and thus investors should construct the hedged portfolio from the multivariate ADVECH-L model with multivariate skewed *t* distribution for dynamic hedging.

Further research on this topic could explore the methodology used to calculate hedging effectiveness and apply it to other financial instruments. Additionally, it may be beneficial for future studies to compare the hedging effectiveness of portfolios constructed with the minimum variance model, EUM model and EUM–VaR model.

Disclosure statement

No potential conflict of interest was reported by the authors.

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