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Full Length Article

Oil hedging with a multivariate semiparametric value-at-risk portfolio

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Abstract

This paper minimizes the risk of Brent oil in a multivariate portfolio, with three risk-minimizing goals: variance, parametric value-at-risk (VaR), and semiparametric value-at-risk. Brent oil is combined with five emerging ASEAN (Association of Southeast Asian Nations) stock indexes and five more developed non-ASEAN indexes. The preliminary dynamic equicorrelation estimates indicate that the ASEAN stock indexes are less integrated and thus potentially better for diversification purposes. The portfolio results show that the ASEAN indexes are better hedges for oil in terms of minimum variance and minimum VaR. However, although the ASEAN indexes have higher extreme risk, we find that a portfolio with these indexes has slightly lower modified VaR than a portfolio with the non-ASEAN indexes. The reason is probably the higher variance and higher equicorrelation of the non-ASEAN indexes, because these inputs affect the value of the modified downside risk of a portfolio. As a complementary analysis, we put a 50 percent constraint on Brent in the portfolios, and then the portfolios with the non-ASEAN indexes have better risk-minimizing results.
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1. Introduction

Countries around the world have found that crude oil is the most important energy commodity for achieving socioeconomic development. However, oil prices are susceptible to huge oscillations due to various global factors, such as economic crisis, regional wars, and uncertainty in supply and demand, and speculation in oil markets (Bassil et al., 2018; Blazsek et al., 2022; Ozcelebi, 2021; Yu et al., 2018). Maitra et al. (2021) assert that oil prices experienced high volatility in recent years for several reasons. First, high oil production levels, coupled with low growth in demand, led to a sharp fall in oil prices in 2016, reaching a 13-year low of $27.10 per barrel. In 2017, the trend reversed because of a simultaneous rise in global demand and a series of geopolitical events at that time. In particular, sanctions imposed on Iran by the US and the decision by Russia and Saudi Arabia to curb oil output in 2018 pushed oil prices to a four-year high of more than $80 per barrel. Soon afterward, the COVID-19 pandemic broke out in 2020, which caused a global economic slowdown, pushing the Brent oil price below $20 in April 2020. The immense oil price fluctuations in a relatively short time attracted the attention of market participants that are linked with oil directly or indirectly (producers, traders, investors, policy makers) from the perspective of asset pricing, risk management, and portfolio allocation (Li et al., 2022).

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We construct multivariate portfolios, combining Brent oil with stock indexes in five ASEAN (Association of Southeast Asian Nations) member countries—Indonesia, Malaysia, Singapore, Thailand, and Philippines—and five non-ASEAN locations (China, Hong Kong, Japan, South Korea, and Taiwan). We consider Brent oil, rather than WTI (West Texas Intermediate) or Dubai/Oman oil, because roughly two-thirds of the crude oil contracts around the world are made in Brent crude, making it the most widely used benchmark oil (Sarwar et al., 2019). In this process, we target different risk measures preferred by participants in the Brent oil market—minimum variance (var), minimum parametric value-at-risk (VaR), and minimum semiparametric VaR, also known as modified VaR (mVaR). We observe the most recent six years, which is punctuated by numerous ups and downs in the Brent oil price. The Brent oil dynamics are depicted on the left-hand side in Fig. 1. Heavy price oscillation by an asset inevitably indicates the presence of risk, and Brent oil has significant risk, according to the plot on the right-hand side of Fig. 1. High risk is particularly conspicuous in the first half of 2020, which is undoubtedly related to COVID-19. At that time, Brent oil had significantly negative returns, creating high daily losses for participants in the Brent oil market.

We combine two groups of stock markets in East Asia, that is, smaller and less developed markets in ASEAN and bigger and more developed non-ASEAN markets, because we want to see which combination of assets in a portfolio with Brent produces better hedging results. The choice of the two different groups of stock markets is intentional, because less developed stock markets are less integrated, which reflects lower mutual correlation between these markets (see, e.g., Chen, 2018; Mensi et al., 2017; Rehman et al., 2022), and the level of correlation is a crucial factor in the portfolio optimization process. Moreover, smaller stock markets are less liquid and thus prone to having outliers, which might imply high losses (Labidi et al., 2018), and this is bad for minimum downside risk portfolios. By contrast developed stock markets are more integrated (see, e.g., Bartram et al., 2007; Stoupos & Kiohos, 2022), which means that they are more correlated, but they also have a higher daily trading volume. More trading in the market mitigates high price swings, which implies fewer negative outliers or downside risk (Ammar & Hellara, 2022). Therefore, by combining two different groups of countries with Brent in a multivariate portfolio, we can determine which factor has the upper hand when the construction of minimum downside risk portfolio is at stake: low mutual correlation between the assets or their low downside risk.

First, we estimate the dynamic conditional equicorrelation (DECO) model of Engle and Kelly (2012) in a preliminary analysis. This model is an extreme case of Engle's (2002) dynamic conditional correlation (DCC) model because correlations in the DECO model are equal across all pairs of assets, but the common equicorrelation changes over time. Instead of calculating and comparing each and every pairwise dynamic correlation to understand the level of interconnectedness between the assets in a portfolio, we use the DECO model, which gives us the bigger picture of interlinks among the selected assets. In other words, estimated equicorrelation is practically an average dynamic correlation between the selected assets. Various researchers have used the DECO model, instead of the classical DCC model, because it can eliminate the computational and presentation difficulties of high-dimension data, which can lead to superior correlation estimates when the pairwise correlations are close to each other (Christoffersen et al., 2014; Kang & Yoon, 2019; Umar et al., 2019; Yilmaz et al., 2015). The DECO model is useful for our analysis because it quantifies the common correlation level between the assets in the portfolios, and this may indicate which portfolio provides better hedging of Brent oil. Also, by looking at the created equicorrelations over time, we can determine in which periods the comovement between assets has higher (lower) convergence.

We try to measure the performance of multivariate portfolios in terms of the lowest risk, which takes different forms: Var, VaR, or mVaR. We apply this comprehensive approach because Var and VaR risk measures have some shortcomings that need to be overcome if we want to produce efficient hedging portfolios. In particular, variance can be a biased risk measure because it gives equal weight to both positive and negative returns, whereas investors are primarily interested in the risk of losses, or downside risk, according to Altun et al. (2017). To address this drawback, we construct a minimum VaR portfolio, which observes the quantile at the left tail of the standard normal distribution. More specifically, we target the portfolio VaR at the 99 percent probability level, which measures an extreme daily loss that investor have a 1 percent chance of confronting. Finding an optimal multivariate portfolio with the lowest VaR is very complex, so relatively few

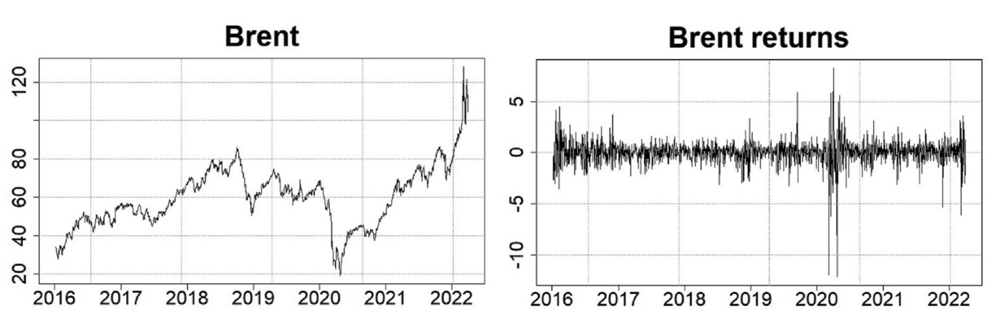

Fig. 1. Empirical dynamics of the Brent oil price and its returns.

papers address this topic (Al Janabi et al., 2019; Gatfaoui, 2019; Vo et al., 2019).

However, VaR is a reliable downside risk measure only under the assumption that a portfolio follows a Gaussian distribution, which is a very strict and unrealistic conjecture. Therefore, VaR usually produces biased risk measures and may lead to erroneous conclusions. This happens because parametric VaR takes into account only the first two moments, whereas the third and fourth moments remain neglected. In this regard, we calculate one more portfolio, which targets the minimum modified VaR. mVaR was introduced by Favre and Galeano (2002) in an attempt to address the crucial disadvantage of a traditional VaR. Semiparametric VaR is based on the Cornish-Fisher expansion (Cornish & Fisher, 1938), which takes into account all four moments of the empirical distribution. More specifically, mVaR penalizes negative characteristics of distribution, such as negative skewness and high kurtosis, and rewards positive characteristics, such as positive skewness and low kurtosis. If the empirical distribution has zero skewness and a kurtosis of 3, then mVaR is reduced to classical parametric VaR. It is even possible that mVaR reports lower downside risk than classical VaR, and this might happen if distribution has low kurtosis and positive skewness.

In order to conduct a more thorough analysis, we hypothesize a situation in which a market participant (oil producer or trader) holds a large amount of oil and thus cannot engage in large-scale diversification. In this portfolio optimization, we limit the amount of Brent oil in a portfolio to 50 percent,[1] and the other 50 percent goes to stock indices. Portfolios with limited Brent oil are calculated with all three risk measures. In this way, we can see whether some changes occur in the choice of auxiliary instruments (ASEAN and non-ASEAN stock indexes) when Brent oil constraints are imposed on the portfolio.

Some recent papers (e.g., Hamdi et al., 2019; Tiwari et al., 2018) have researched the relationship between Brent and stock markets with the implications for the portfolio. However, to the best of our knowledge, this paper is the first to combine Brent oil with ASEAN and non-ASEAN stock indexes in a multivariate portfolio, with the goal of reducing different types of risk. We emphasize in particular the method that enables us to minimize semiparametric VaR in a multivariate portfolio. This has never been done before and thus is our primary motive for this research. In this regard, our study proposes a new idea about how to measure and deal with extreme risk in a globally very important oil market.

The rest of the paper, after this introduction, is structured as follows. Section 3 presents an overview of the literature. Section 3 explains the DECO-DCC model and portfolio optimization processes. Section 4 contains the dataset and preliminary findings. Section 5 presents the results of the minimum-risk portfolios created. Section 6 shows the results when Brent oil restrictions are imposed. Section 7 discusses the results, and Section 8 concludes.

[1] This percentage of oil in a portfolio is arbitrary.

2. Literature review

This section presents recent papers that address the topic of oil hedging. For example, Olstad et al. (2021) research the construction of the optimal portfolio and time-varying correlation between the volatility of the two oil benchmarks (Brent and WTI) and the six currencies of the major oil importers (euro, Indian rupee, and Japanese yen) and oil exporters (Canadian dollar, British pound sterling, and Norwegian kroner). They use a diagonal-BEKK (Baba, Engle, Kraft, and Kroner) model, reporting that risk reduction based on the optimal portfolio weight strategy is primarily beneficial for oil volatility investors, whereas currency volatility investors achieve better hedging using the optimal hedge ratio strategy. Salisu et al. (2021) examines the role of gold as a safe haven or hedge against crude oil price risks, employing the asymmetric vector autoregressive moving average (VARMA-GARCH) model. They also account for the impact of COVID-19 pandemic in the analysis, as we do. They find gold a significant safe haven against oil price risks, and their optimal portfolio and hedging analyses confirm the hedging effectiveness of gold against risk associated with oil. Wang et al. (2022) investigate the nonlinear oil-gold relationship using the extreme value theory (GARCH-EVT-VaR) model and a continuous wavelet transform, and they use extreme bound analysis (EBA). The results indicate that gold could hedge against oil price fluctuations across time horizons nearly half the time. They assert that gold can provide strong safe-haven power against extreme oil price movements in about half the cases, but this performance is better in medium- and long-term time horizons. Živkov et al. (2022) construct four minimum-variance multivariate portfolios, combining energy commodities (Brent oil, WTI oil, gasoline, and natural gas) with four precious metals. They address different possible situations for market participants, imposing constraints on the energy share in portfolios of 30 percent and 70 percent. They report that the highest share in all portfolios is in gold, but in two cases a tiny share is in palladium. Silver and platinum have no share of portfolios whatsoever. They also find more risk reduction in 30 percent portfolios than in 70 percent portfolios, which means that investors who want to pursue a less-risky energy portfolio should include more gold.

Adekoya and Oliyide (2020) conduct a robust analysis of the effectiveness of seven commonly traded industrial metals in providing cover for investors against oil market risks. They use conventional bivariate analysis and then a multivariate analysis, reporting that the nature of shocks, whether demand or supply based, determines the hedging ability of industrial metals. They assert that oil supply shocks cannot be hedged by metals regardless of the estimation model, but all three other demand-based oil shocks can be effectively hedged by virtually all the metals. Lin et al. (2021) studied risk spillovers and hedge strategies between three global crude oil markets (WTI, Brent, and Dubai) and three stock indexes (Chinese Shanghai stock index, S&P 500 index, and Stoxx European 600 index). They applied a multivariate long memory and asymmetry GARCH framework that integrates state-dependent regime switching in the mean process with multivariate long memory and asymmetry GARCH in the variance process. As for construction of the portfolio, calculated dynamic hedge effectiveness showed that the regime-switching process, combined with long memory and asymmetry behavior, seems to be a plausible and feasible way to conduct hedge strategies between the global crude oil markets and stock markets. Belhassine and Karamti (2021) research volatility spillovers and hedging effectiveness between the oil and the stock markets in top oil-importing (the United States, China, and India) and oil-exporting countries (Saudi Arabia, Russia, and Canada) over different investment horizons. They use a wavelet-based multivariate GARCH framework, as well as a cross-wavelet coherence analysis, as an alternative method. All calculated hedge ratios indicated that all selected indices are good hedges for oil. In particular, India and China offer the most profitable hedging opportunities with oil over all investment horizons.

3. Methodologies

3.1. DECO-DCC GARCH model

Before constructing the portfolio, we calculate the dynamic correlation between the assets in the two portfolios with Brent. This gives us a preliminary insight, which stock indexes (ASEAN or non-ASEAN) have less correlation with Brent. The results could indicate which portfolio might have lower risk because the level of correlation is very important input in the portfolio optimization procedure. To this end, we do not rely on the classical dynamic conditional correlation model by Engle (2002) because this model has the computational and presentation difficulties of high-dimension data, when many assets are combined into a single portfolio. Instead, we resort to a simpler version of the DCC model, which is called the dynamic equicorrelation model of Engle and Kelly (2012). The DECO-DCC model assumes that all pairwise correlations in the DCC framework are equal, but their common equicorrelation is time varying, which makes estimation process much easier and quicker.

We want to be precise in the DECO-DCC modelling, so we estimate this model using both symmetric and asymmetric GARCH models in univariate specifications in both groups of assets. The best model is determined by the lowest Akaike information criterion (AIC) value, and, from this model, we calculate equicorrelation. Because symmetric GARCH model is nested in the asymmetric GJR-GARCH model, we present mean and variance equation specifications only of the latter one in Equations (1) and (2).

$$y_t = C + \phi y_{t-1} + \varepsilon_t;\ \varepsilon_t \sim z_t\sqrt{\sigma_t^2} \tag{1}$$

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1};\ I_{t-1} = \begin{cases} 1\ if\ \varepsilon_{t-1} < 0 \\ 0\ if\ \varepsilon_{t-1} > 0 \end{cases} \tag{2}$$

The mean equation has AR(1) form, which is enough lag order to handle the serial correlation problem in the selected time series. C and c are constants in the mean and variance equations. y_t denotes a 6×1 vector of stock indexes and Brent oil, whereas ε_t is 6×1 vector of error terms. Symbol z_t describes an independently and identically distributed process in the univariate GARCH model. In conditional variance equations, parameter β describes the persistence of volatility, while α measures the ARCH effect. Parameter γ gauges an asymmetric effect, that is, if $\gamma > 0$ then negative shocks affect volatility more than positive shocks, and vice-versa.

The DCC model is designed to ensure the positive definiteness of the variance-covariance matrix (H_t):

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{3}$$

where $R_t = [\rho_{ij,t}]$ is the conditional correlation matrix, whereas the diagonal matrix of the conditional variances is given by $D_t = dig(h_{1,t}\ldots, h_{n,t}$. According to Engle (2002), the right-hand side of Equation (3) can be modelled directly with the following dynamic correlation structure:

$$R_t = \left(Q_t^*\right)^{-1/2} Q_t \left(Q_t^*\right)^{-1/2} \tag{4}$$

$$Q_t^* = diag(Q_t) \tag{5}$$

$$Q_t = \left[q_{ij,t}\right] = (1-a-b)S + a u_{t-1} u_{t-1}' + b Q_{t-1} \tag{6}$$

where $u_t = [u_{1,t}, \ldots, u_{n,t}]'$ is the standardized residuals, $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$. $S = [s_{i,j}] = E[u_t u_t']$ is the $n \times n$ unconditional covariance matrix of u_t, while a and b are nonnegative scalars satisfying $a + b < 1$. The resulting model is called the DCC model. Aielli (2013) proves that the estimation of the covariance matrix Q_t in this way is inconsistent because $E[R_t] \neq E[Q_t]$ and suggests using the consistent DCC (cDCC) model for the correlation-driving process:

$$Q_t = (1-a-b)S^* + a\left(Q_{t-1}^{*1/2} u_{t-1} u_{t-1}' Q_{t-1}^{*1/2}\right) + b Q_{t-1} \tag{7}$$

where S^* is the unconditional covariance matrix of $Q_{t-1}^{*1/2} u_t$. Engle and Kelly (2012) recommend modelling ρ_t using the cDCC process to obtain the conditional correlation matrix Q_t and then taking the mean of its off-diagonal elements. They call this approach the dynamic equicorrelation model, and the scalar equicorrelation is defined as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(J_n' R_t^{cDCC} J_n - n\right) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{8}$$

where $q_{ij,t} = \rho_t^{DECO} + a_{DECO}(u_{i,t-1}u_{j,t-1} - \rho_t^{DECO}) + b_{DECO}(q_{ij,t} - \rho_t^{DECO})$, which is the $(i,j)^{th}$ element of the matrix Q_t from the cDCC model. Scalar equicorrelation is then used to estimate the conditional correlation matrix:

$$R_t = (1-\rho_t) I_n + \rho_t J_n \tag{9}$$

where J_n is $n \times n$ matrix of ones, and I_n is the n-dimensional identity matrix. This process enables us to represent the degree of comovement in a group of assets in a portfolio with a single time-varying correlation coefficient. In order to ensure reliable equicorrelations, all the DECO-DCC models are estimated using the two different multivariate distribution functions: normal and Student *t*.

3.2. Portfolio optimization with different risk-minimizing goals

We combine Brent oil with the five ASEAN and non-ASEAN stock indexes in the two multivariate portfolios, which have the three different goals: minimum variance, minimum value-at-risk, and minimum modified value-at-risk. Performing the portfolio optimization procedure originally introduced by Markowitz (1952), we try to determine the optimal combination of assets in a portfolio that fulfills these goals. The starting point in this task is the construction of a minimum-variance portfolio, which is achieved by solving Equation (10):

$$min\ \sigma_p^2 = min\sum\nolimits_{i=1}^{n} w_i^2\sigma_i^2 + \sum\nolimits_{i=1}^{N}\sum\nolimits_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j} \tag{10}$$

where σ_p^2 is portfolio variance, σ_i^2 is variance in a particular asset i, w_i is the calculated weight of asset i in a portfolio, whereas $\rho_{i,j}$ is correlation coefficient between a specific pair of assets (i and j). The necessary constraints in every multivariate portfolio optimization process are that the sum of all weights is one, whereas the individual weights are between zero and one.

$$\sum\nolimits_{i=1}^{N} w_i = 1;\ 0 \le w_i \le 1 \tag{11}$$

Every portfolio with minimum variance has a corresponding mean value, a weighted average portfolio return (r_p), which can be calculated as in Equation (12).

$$r_p = \sum\nolimits_{i=1}^{n} w_i r_i \tag{12}$$

The first (r_p) and second (σ_p) moments in Equations (12) and (10) are used to construct the minimum VaR portfolio, where $VaR_p = r_p + Z_\alpha\sigma_p$. Z_α is the left quantile of the normal standard distribution. Minimum VaR_p portfolio optimization is written as in Equation (13):

$$\min VaR_p(w),\ \sum\nolimits_{i=1}^{n} w_i r_i \tag{13}$$

However, a portfolio with the minimum parametric VaR can be regarded as accurate only if its empirical distribution has Gaussian characteristics, which is a very strict and unlikely assumption. This is the case because parametric VaR takes into account only the first two moments (mean and variance), and skewness and kurtosis are disregarded (see He et al., 2020; Živkov et al., 2021). A portfolio with minimum parametric VaR as a goal yields an accurate risk assessment only if its skewness is nearly zero, and kurtosis is around 3, which is a very improbable scenario when daily time-series are in question. In order to circumvent this potential bias in a min-VaR portfolio, we also calculate a min-mVaR portfolio, which overcomes this issue, because it takes into account all four moments of the empirical distribution. Accordingly, mVaR for a short position is defined as in Equation (14), whereas a minimum mVaR portfolio optimization is given in Equation (15):

$$mVaR_\alpha = r_p + Z_{CF,\alpha}\sigma_p \tag{14}$$

$$\min mVaR_p(w),\ \sum\nolimits_{i=1}^{n} w_i r_i \tag{15}$$

where $Z_{CF,\alpha}$ Îis the non–normal distribution percentile adjusted for skewness and kurtosis according to the Cornish–Fisher expansion:

$$Z_{CF,\alpha} = Z_\alpha + \frac{1}{6}(Z_\alpha^2 - 1)S + \frac{1}{24}(Z_\alpha^3 - 3Z_\alpha)K - \frac{1}{36}(2Z_\alpha^3 - 5Z_\alpha)S^2 \tag{16}$$

where S and K are measures of skewness and kurtosis in a portfolio.

As a complementary analysis, we show what the portfolios would appear if we imposed a minimum 50 percent Brent oil constraint in the portfolio optimization process. These portfolios should reflect the position of oil producers or traders, who hold large amounts of oil, which limits them from pursuing a full-scale diversification strategy. Accordingly, the weight restriction of oil and stock indexes take the following form:

$$w^{oil} \ge 0.5;\ 0.5 \ge w_i^{stock\ index} \ge 0 \tag{17}$$

Finally, we evaluate the risk-reduction performance of all the minimum-risk portfolios created with hedge effectiveness indexes (HEI). In particular, portfolio HEI_{RM} is calculated as follows:

$$HEI_{RM} = \frac{RM_{unhedged} - RM_{hedged}}{RM_{unhedged}} \tag{18}$$

where RM denotes the particular risk measure of a portfolio, that is, Var, VaR, or mVaR. *unhedged* refers to investment only in Brent oil, whereas *hedged* indicates investment in portfolios with ASEAN and non-ASEAN stock indexes. When HEI is closer to 1, hedging effectiveness is higher, and vice-versa.

4. Dataset and preliminary findings

4.1. Descriptive statistics of the selected assets

We construct multivariate portfolios using daily Brent oil short-maturity futures and stock indexes in the ASEAN and non-ASEAN East Asian countries. We choose futures, rather than spot prices, of Brent oil because futures process new information more quickly and incorporate expectations, which makes these prices more realistic. Moreover, futures markets are highly liquid, with low trading costs, which makes futures very convenient for diversification purposes. You and Daigler (2013) assert that purchasing and selling futures is similar to purchasing and selling stocks, which means that portfolio theory can be applied to the futures market with no problem. In addition, the movement of short-term futures is much like that of spot price dynamics, which implies that conclusions about futures portfolio can be applied to spot price portfolios in a straightforward way. This is important for market participants who works with real assets, such as oil producers and traders.

Brent oil futures are combined in two portfolios consisting of ASEAN and non-ASEAN stock indexes. The five ASEAN indexes are the IDX (Indonesia), the KLSE (Malaysia), the FTWISGPL (Singapore), the SET (Thailand), and the PSEi (Philippines) and the non-ASEAN indices are the CSI1000 (China), the Hang Seng (Hong Kong), the NIKKEI225 (Japan), the KOSPI (South Korea), and the TPEx50 (Taiwan). The data span more than six years, January 2016 to March 2022, and all the data come from the website nvesting.com. We synchronize Brent oil separately with the two groups of stock indexes, in which each time series in combination with the ASEAN indexes has 1334 observations, and in non-ASEAN group, it has 1332. All the time series are transformed into log-returns ($r_{i,t}$) based on the equation: $r_{i,t} = 100 \times log(P_{i,t}/P_{i,t-1})$, where P_i is the price of a particular asset. The descriptive statistics of all the time series are listed in Table 1.

Table 1 comprises the first four moments: the Ljung-Box Q test for level and squared returns, the DF-GLS test of stationarity, and parametric and semiparametric downside risk assessments of every asset. VaR and mVaR are also included in the descriptive statistics because we construct two minimum downside risk portfolios in addition to a classical Markowitz minimum variance portfolio. For this reason, it is important to gain insights into the downside risk of every asset, because individual levels of downside risk determine the position of a particular asset in a portfolio.

Brent oil has the highest risk among all the stock indices, not only in terms of variance but also in terms of the two downside risks. This means that portfolio optimization will probably reduce Brent oil to very low levels in all the portfolios. The VaR level of oil is the highest because oil has the highest standard deviation, and the second moment is the key component in calculating parametric VaR. This means that the levels of standard deviations and VaRs are almost perfectly proportional. In the group of ASEAN indices, the Filipino PSEi index has the highest VaR and among the non-ASEAN indices, the Chinese CSI100 has the highest, and both indices also have the highest standard deviation. However, this connection cannot be made between variance and mVaR because mVaR includes all four moments in the calculation, and the levels of skewness and kurtosis are not aligned proportionately with variance. For instance, among all the ASEAN indices, PSEi has the highest VaR (−1.317), followed by SET (−1.018). However, with respect to mVaR, SET has higher downside risk because it has higher kurtosis and more negative skewness, although SET has a lower standard deviation than PSEi.

Our examination of the two groups of indices reveals that the bigger and more developed non-ASEAN markets have higher variance than the smaller and less developed ASEAN counterparts. This finding is probably linked to the fact that the developed stock markets have higher trading volume than the ASEAN markets. In other words, a higher trading volume, which reflects the information flow on the market, can induce higher volatility, and vice-versa. This findings is consistent with that of Nishimura (2016) and Tissaoui et al. (2021). Nishimura documents that volume has a significant positive influence on volatility across China's stock index and index futures markets. However, Tissaoui et al. describe a significant mutual effect between liquidity risk and realized volatility in the Saudi stock exchange after the effect of local COVID-19 cases is omitted. Because the ASEAN indices have lower variance than the non-ASEAN counterparts, the multivariate portfolio with the ASEAN indices might have lower variance.

At the same time, it is evident that the less developed stock markets have higher kurtosis, which translates into higher mVaR risk. The findings by Xu et al. (2019) are in line with our findings. They investigate the heterogeneous effect of liquidity on volatility in the futures market of Chinese stock market indexes using the quantile regression method and find that illiquidity leads to an increase in volatility. High volatility is actually an outlier, responsible for high kurtosis and high mVaR downside risk, and this is what we find in the less

Table 1
Descriptive statistics of the time series.

	Mean	St. dev.	Skew.	Kurt.	LB(Q)	LB(Q^2)	DF-GLS	VaR	mVaR
Brent	0.016	1.152	−1.882	24.060	0.022	0.000	−4.326	−2.662	−5.521
Panel A: ASEAN stock indices									
IDX	0.008	0.438	−0.148	13.821	0.000	0.000	−5.727	−1.010	−2.077
KLSE	0.000	0.312	−0.325	14.132	0.048	0.000	−3.252	−0.727	−1.468
FTWISGPL	0.006	0.431	−0.263	20.855	0.000	0.000	−24.164	−0.997	−2.319
SET	0.008	0.441	−1.111	20.942	0.000	0.000	−3.345	−1.018	−2.564
PSEi	0.002	0.567	−1.561	19.754	0.000	0.000	−39.661	−1.317	−2.534
Panel B: Non-ASEAN stock indices									
CSI1000	−0.013	0.668	−0.898	7.501	0.036	0.000	−2.654	−1.567	−1.736
Hang Seng	0.002	0.530	−0.115	7.406	0.008	0.000	−6.080	−1.230	−1.742
NIKKEI225	0.020	0.553	−0.065	8.723	0.006	0.000	−7.684	−1.266	−1.988
KOSPI	0.017	0.448	−0.527	13.061	0.004	0.000	−6.027	−1.026	−1.907
TPEX50	0.022	0.617	−0.838	7.090	0.426	0.000	−34.601	−1.413	−1.555

Notes: JB means Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) tests refer to the *p*-values of Ljung-Box Q-statistics of the level and squared returns for 10 lags. Assuming only constant, the 1% and 5% critical values for the DF-GLS test with 10 lags are −2.566 and −1.941, respectively.

developed ASEAN markets. Consistent with our earlier conclusion, we assume that a portfolio with the non-ASEAN indices will probably have less extreme risk, as measured by mVaR.

However, this nothing has to be true because mutual correlation between assets also needs to be accounted for in a portfolio optimization procedure, in which having less correlation between assets in a portfolio produces better hedging results. The estimated equicorrelations in the next section reveal which markets are less integrated and thus more suitable for portfolio diversification.

The Ljung-Box Q test indicates that only the TPEX50 has no autocorrelation problems, whereas heteroscedasticity is pervasive in all the other assets. This means that the AR(1)-GJR-GARCH(1,1) model can handle these issues in the DECO-DCC model. The DF-GLS test suggests that all the time-series are stationary, which is a necessary precondition for a GARCH estimation.

4.2. Equicorrelation findings

This section presents the results of the estimated DECO models. In order to produce accurate equicorrelation results, we estimate the DECO models with different specifications. First, we change univariate models, that is, symmetric GARCH and asymmetric GJR-GARCH models, and estimate the DECO models with the two multivariate distributions, normal and Student's *t*. In other words, we estimate eight different DECO models. This procedure tests for robustness in the estimation process, and the best model is indicated by the lowest AIC value. Table 2 gives the AIC results.

In the table, the best DECO-DCC specifications of both portfolios are the asymmetric GJR-GARCH model and multivariate Student's *t* distribution. This means that the asymmetric GJR-GARCH model is better than the symmetric GARCH model, probably because we are dealing with daily stock indexes and oil, in which an asymmetric effect is common. However, multivariate a Student's *t* distribution indicates that both equicorrelations have extreme values or heavy tails, which are clearly visible in Fig. 2. Following Yilmaz et al. (2015), we filter both equicorrelations with the Hodrick and Prescott (1997) process in order to illustrate the trend component. Trends are depicted with the red line in Fig. 2, in which both average equicorrelations are relatively low, 0.271 and 0.326. However, the equicorrelation is 5.5 percent lower in the ASEAN-Brent combination than in the counterpart with the non-ASEAN indexes. Therefore, we can conclude that the ASEAN indexes are better for hedging purposes. Also, Fig. 2 indicates that the highest peak in the left plot was reached at the beginning of the pandemic (almost 70%), whereas in the right plot, this happened during the global financial crisis (around 80%).

Table 3 shows the estimated parameters of the DECO-DCC-GJR-GARCH model for the two groups of assets. Not all the time series have ARCH effects, but all the markets show volatility persistence because all the β parameters are highly statistically significant. The Brent market, three of the five ASEAN countries, and four of the five non-ASEAN countries have asymmetric effects. All statistically significant γ parameters are positive, which implies that negative shocks increase volatility more than positive shocks. This is a common finding in stock markets (see, e.g., Beckmann et al., 2019; Jiang et al., 2019). Moreover, all γ parameters are relatively high in the non-ASEAN markets, whereas we find high γ parameter only in Indonesia. A high asymmetric effect is expected in developed non-ASEAN markets, because they are more liquid than the ASEAN stock exchanges.

In Panels C and F in Table 2, the estimated a_{DECO} parameters are positive and significant, which means that market shocks affect equicorrelations. In addition, b_{DECO} parameters are also positive and significant, which indicates that equicorrelations are dependent on past correlations. Statistically significant DECO-DCC parameters signal the appropriateness of this multivariate model. The Ljung–Box test statistics of the standard and squared residuals in the Panels B and E fail to reject the null hypotheses of no serial correlation and heteroscedasticity in all cases, which suggests that the models are well specified. All the M-shaped parameters are highly statistically significant, which indicates that the Student's *t* distribution describes the distribution of both equicorrelations very well.

Based on the preliminary findings, ASEAN markets have less variance and less equicorrelation, which gives us a good reason to believe that the ASEAN portfolio can probably hedge Brent better in terms of variance and VaR. However, non-ASEAN indexes have less mVaR, but higher equicorrelation, thus we cannot assume that the portfolio with non-ASEAN indexes has less modified downside risk. The next section presents the results of the portfolios created, giving a clear answer as to which portfolio is better, taking heterogeneous risk measures into account.

5. Empirical results of portfolio construction

This section presents the results of the multivariate optimal portfolios calculated, using the different risk measures—Var,

Table 2
Calculated AIC values of different DECO-DCC models.

	Portfolios with ASEAN indexes				Portfolios with non-ASEAN indexes			
	Multivariate N		Multivariate St		Multivariate N		Multivariate St	
	GARCH	GJR-GARCH	GARCH	GJR-GARCH	GARCH	GJR-GARCH	GARCH	GJR-GARCH
AIC value	6.325	6.306	5.850	**5.821**	9.026	8.947	8.539	**8.521**

Note: Values in boldface indicate the lowest AIC.

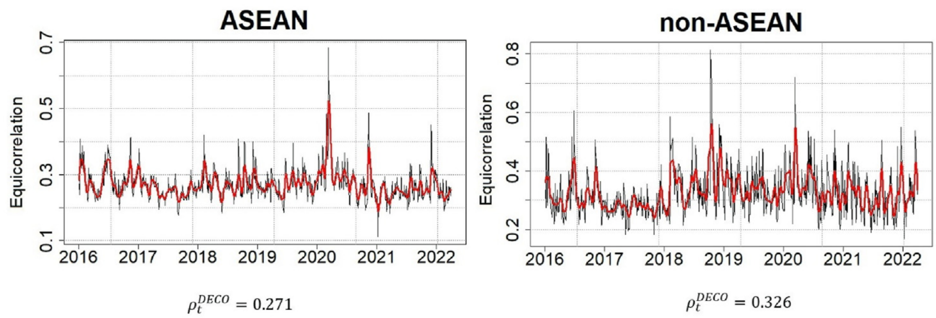

Fig. 2. Estimated equicorrelations of the two portfolios, *Note*: The red line is a trend component of the estimated equicorrelations, calculated with the Hodrick and Prescott (1997) filter.

Table 3
Parameter estimates of the DECO-DCC-GJR-GARCH models.

	ASEAN portfolio					
	Brent oil	IDX	KLSE	FTWISGPL	SET	PSEI
Panel A. GJR-GARCH parameter estimation with ASEAN stock indices						
α	0.087***	0.065**	0.036**	0.071	0.049***	0.050
β	0.825***	0.698***	0.931***	0.786***	0.897***	0.855***
γ	0.110*	0.254***	0.053**	0.067	0.078	0.097**
Panel B. Diagnostic tests						
LB(Q)	0.577	0.532	0.874	0.181	0.554	0.338
LB(Q^2)	0.809	0.261	0.163	0.995	0.973	0.823
Panel C. Estimates of DECO model						
a_{DECO}	0.057*					
b_{DECO}	0.751***					
M-shape	7.373***					
	Non-ASEAN portfolio					
	Brent oil	CSI1000	Hang Seng	NIKKEI225	KOSPI	TPEX50
Panel D. GJR-GARCH parameter estimation with non-ASEAN stock indices						
α	0.037***	0.054***	0.011	0.014	0.084***	0.046**
β	0.823***	0.916***	0.896***	0.820***	0.717***	0.781***
γ	0.188**	−0.013	0.100***	0.238***	0.169**	0.200**
Panel E. Diagnostic tests						
LB(Q)	0.240	0.844	0.221	0.359	0.974	0.109
LB(Q^2)	0.739	0.988	0.939	0.327	0.391	0.793
Panel F. Estimates of DECO model						
a_{DECO}	0.128***					
b_{DECO}	0.641***					
M-shape	6.547***					

Notes: LB(Q) and LB(Q^2) indicate *p*-values at 10 lags. ***, **, and * statistical significance at the 1%, 5%, and 10% level, respectively.

VaR, and mVaR—as targets. Table 4 lists the optimal weight for all the assets in the portfolios. The portfolios with the minimum Var and VaR have the same structure in terms of asset weights calculated, whereas the portfolio with the minimum mVaR has a different weight composition. This applies to both the ASEAN and non-ASEAN portfolios. This is the case because parametric VaR only uses the first two moments for calculation, but the standard deviation has a crucial role in this process. This means that the values of variance and VaR are almost perfectly proportional, and this relation applies to single assets, shown in Table 1, as well as to the construction of portfolios. This finding is consistent with that of Abuaf et al. (2018), who constructs multivariate minimum-Var and minimum-VaR portfolios and concludes that these portfolios have an identical structure.

However, we go even further and additionally calculate a very complex portfolio that targets the minimum modified value-at-risk. The portfolio with mVaR adds the third and fourth moments to the calculation, which makes portfolio optimization very complex. Skewness and kurtosis are not proportional to variance, and this is why the structure of mVAR portfolios differs significantly from that of the Var and VaR portfolios (see Table 4).

In the previous section, we calculated equicorrelations between the assets of the two portfolios, but these average correlations are not very helpful for explaining the share of a particular asset in a portfolio. For this reason, we show pairwise Pearson correlations between the assets of the two portfolios in Table 5. By combining the results in Tables 4 and 5, we can reasonably explain the specific share of an asset in the

Table 4
Calculated weights of the selected assets in the two multivariate portfolios.

	Portfolios with ASEAN indexes				Portfolios with non-ASEAN indexes		
	Var	VaR	mVaR		Var	VaR	mVaR
Brent oil	1%	1%	1%	Brent oil	7%	7%	6%
IDX	17%	17%	34%	CSI1000	18%	18%	39%
KLSE	61%	61%	40%	Hang Seng	5%	5%	7%
FTWISGPL	12%	12%	26%	NIKKEI225	13%	13%	0%
SET	9%	9%	0%	KOSPI	49%	49%	33%
PSEi	0%	0%	0%	TPEX50	8%	8%	15%
Σ	100%	100%	100%	Σ	100%	100%	100%

portfolios. In Table 4, Brent oil has a very low share in both portfolios, regardless of which risk measure is targeted, even though Brent oil does not have a high correlation with the ASEAN and non-ASEAN indexes (see Table 5). However, on all the Asian stock indexes, Brent oil is the riskiest asset, and this is the main reason that the portfolio optimization procedure assigns such a low share to oil in both portfolios. In the ASEAN portfolio, the Malaysian KLSE index has the highest share 61 percent in the Var and VaR portfolios, and 40 percent in the mVaR portfolio. The KLSE has the lowest standard deviation and the lowest VaR and mVaR, and these are the primary reasons that it has the highest share in all three portfolios. The Indonesian IDX index has the second-highest share (17% in the Var and VaR portfolios, and 34% in the mVaR portfolio), and the IDX has the fourth-highest risk, that is, after FTWISGPL index in the ASEAN portfolio. The IDX is better positioned than the Filipino index in all three portfolios probably because it has a lower average correlation (0.358) than the FTWISGPL (0.374). SET has 9 percent in the Var and VaR portfolios because of its relatively high standard deviation (0.441), but more importantly because SET has the highest average correlation with other assets in the portfolios (0.394). In the mVaR portfolio, SET has a zero share because it has the highest kurtosis and the second-highest skewness. PSEi has a zero share in all three portfolios because it has the highest standard deviation and the second-highest mVaR, just after SET.

In the portfolios with the non-ASEAN indexes, the share of oil is somewhat higher, 7 percent in the Var and VaR portfolios, and 6 percent in the mVaR portfolio. These results can explain two factors. The non-ASEAN indexes have a higher standard deviation and lower pairwise correlation with oil than their ASEAN counterparts, and, therefore, an optimization procedure gives oil a higher share in the Var and VaR portfolios. Non-ASEAN indexes have lower mVaR values than ASEAN indexes, nevertheless, in the combination with non-ASEAN indexes, oil has a significantly higher share, 6 percent, than the ASEAN portfolio, 1 percent. The results indicate that the lower pairwise correlation of oil (0.145) plays a dominant role in explaining the significantly higher share of oil in the non-ASEAN portfolio, in which auxiliary assets have less modified downside risk. KOSPI has the highest share in the Var and VaR portfolios, 49 percent, because it has the lowest standard deviation. Surprisingly, the Chinese CSI1000 has the second-largest share, 18 percent, although this index has the highest standard deviation (0.668). The explanation is the very low average correlation of the CSI100 (0.276), and this is why it has the second-highest share in the Var and VaR portfolios. However, in the mVaR portfolio, the situation is different, that is, the CSI1000 is in first place with 39 percent, and the KOSPI is in second place with 33 percent. This happens because the KOSPI has the highest kurtosis (13.061), and the CSI1000 has one of the lowest (7.501). The NIKKEI has the third-highest share in the Var and VaR portfolios, 13 percent, because the Japanese index has the third-lowest standard deviation (0.553). However, the NIKKEI225 has no share in the mVaR portfolio because it has the

Table 5
Pairwise Pearson correlations between the selected stock indexes.

		Brent	IDX	KLSE	FTWISGPL	SET	PSEI	Average ρ
ASEAN stock indexes	Brent	1	0.139	0.131	0.181	0.224	0.082	0.151
	IDX	0.139	1	0.408	0.381	0.395	0.465	0.358
	KLSE	0.131	0.408	1	0.463	0.462	0.432	0.379
	FTWISGPL	0.181	0.381	0.463	1	0.500	0.343	0.374
	SET	0.224	0.395	0.462	0.500	1	0.389	0.394
	PSEI	0.082	0.465	0.432	0.343	0.389	1	0.342
		Brent	CSI1000	Hang Seng	NIKKEI225	KOSPI	TPEX50	Average ρ
non-ASEAN stock indexes	Brent	1	0.119	0.201	0.161	0.131	0.114	0.145
	CSI1000	0.119	1	0.428	0.240	0.279	0.313	0.276
	Hang Seng	0.201	0.428	1	0.536	0.640	0.461	0.453
	NIKKEI225	0.161	0.240	0.536	1	0.614	0.440	0.398
	KOSPI	0.131	0.279	0.640	0.614	1	0.516	0.436
	TPEX50	0.114	0.313	0.461	0.440	0.516	1	0.369

highest mVaR; KOSPI has a high share in the portfolio, 33 percent, and is highly correlated with the NIKKEI225 (0.614). Hang Seng has the highest correlation with other indexes (0.453), and this is why it has the lowest share in all three portfolios, although it is not the riskiest index. The TPEX50 has a relatively high standard deviation, mVaR, and average correlation, and this is why its share is the second lowest in all portfolios, after Hang Seng.

Fig. 3 illustrates the VaR and mVaR efficient frontier lines of the portfolios, along with the spatial position of all assets in them. Plots of the Var portfolios are not presented because they are identical to the VaR plots. In the figure, the positions of some points differ between the VaR and mVaR plots, because VaR and mVaR risks are not synchronized. Point (7) is rather far from point (1) in all the plots, which clearly indicates that the portfolios with both ASEAN and non-ASEAN indexes are very good at reducing the extreme risk of Brent oil. However, less developed ASEAN indexes are little bit better at this task, when all three risk measures are taken into account.

6. Imposing brent oil constraints on minimum-risk portfolios

This section serves as complementary analysis, in which we explore what minimum-risk portfolios look like if share restrictions were imposed on the riskiest asset in the portfolios: Brent oil. The idea is borrowed from a recent paper by Živkov et al. (2022), and we hypothesize a situation in which a market participant holds a minimum of 50 percent in Brent oil, with the remainder of the portfolio in the selected Asian indexes. In the previous section, portfolio optimization reduces Brent oil to very low level because it is very risky asset. This makes it very hard for investors who hold a significant amount in oil to pursue full diversification of their portfolio. Therefore, a 50 percent Brent oil portfolio is more realistic for market agents who work with oil on a daily basis. Accordingly, we perform the portfolio optimization procedures again with the oil limitation, and the shares of assets calculated are in Table 6.

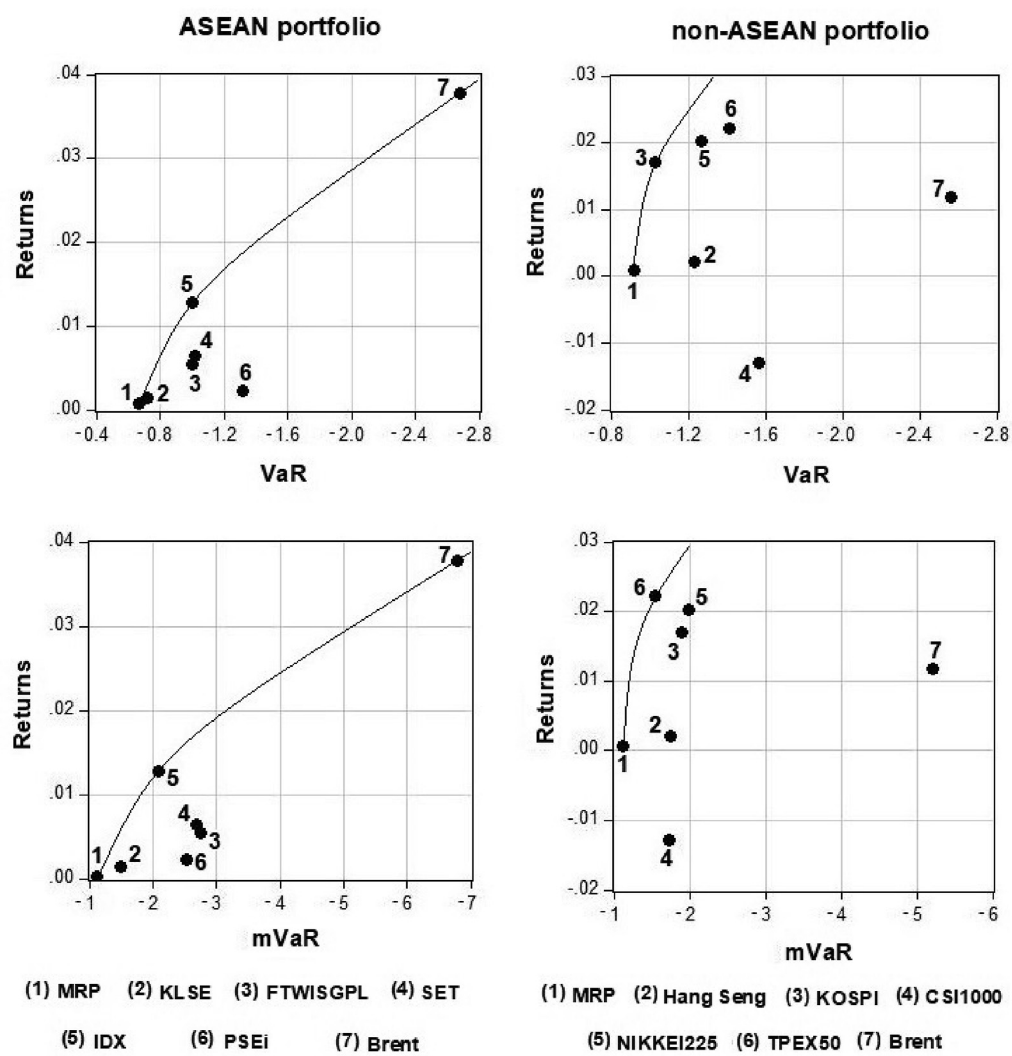

Fig. 3. Plots of VaR and mVaR efficient frontier lines, *Note:* MRP means "minimum-risk portfolio."

The Var and VaR portfolios have the same structure, as in the previous section, which is expected. In combination with the ASEAN indexes, the Malaysian KLSE has the highest share in all three portfolios because this index is the least risky, regarding all three risk measures, and it has a relatively low average correlation with the other assets in the portfolio. In the Var and VaR portfolios, IDX and PSEi have shares of 5 percent and 1 percent, respectively, probably because they have very low correlation with other assets. The mVAR portfolio comprises only oil and KLSE.

In the non-ASEAN portfolio, KOSPI has the highest share when the targets are Var and VaR. The explanation is the same as in the case of the KLSE index, that is, KOSPI is the least risky asset. The Chinese CSI100 and Taiwanese TREX50 indexes have shares of 10 percent and 4 percent, respectively, arguably because they have the lowest average correlations. However, in the mVaR portfolio, CSI1000 takes the highest share, 42 percent, because it has the least modified downside risk, and KOSPI follows with 8 percent because it has relatively low correlation with both oil and the CSI1000 index.

7. Discussion of the results

The previous two sections present the structure of the portfolios created, and this section presents the characteristics of each portfolio, with a comparison of them. Table 7 contains descriptive statistics of the portfolios created without constraints. It shows the variations in the first four moments, as well as VaR and mVaR, when the portfolios have different objectives. In Table 3, the Var and VaR portfolios have the same structure, but the skewness and kurtosis of these portfolios slightly diverge in Table 7 because shares of assets differ at the third decimal in these two portfolios, which is not seen in Table 3. The Var and VaR portfolios have lower variance than the mVaR portfolio, which is expected, and the mVaR portfolio has lower modified VaR than its Var and VaR counterparts. This means that all portfolio optimizations are efficient. Also, it is clear that the variance (0.287 and 0.396) and VaR (−0.662 and −0910) of the two portfolios created is lower than any asset variance, and the mVaR of the portfolios (−1.107 and −1.117) is lower than the mVaR of any other asset. This means that all assets are placed within efficient frontier lines, which is illustrated in Fig. 3, confirming well-executed portfolio optimizations. In addition, the difference between VaR and mVaR in the two optimal portfolios is significant, which means that the third and fourth moments play an important role in determining downside risk. This is a clear sign that VaR seriously underestimates extreme risk, which could lead to erroneous decisions.

Table 7
Descriptive statistics, VaR, and mVaR of the portfolios created without constraints.

	Portfolios with ASEAN indexes			Portfolios with non-ASEAN indexes		
	Var	VaR	mVaR	Var	VaR	mVaR
Mean	0.001	0.001	0.000	0.001	0.001	0.001
Variance	0.287	0.287	0.301	0.396	0.396	0.426
Skewness	−0.963	−0.991	−1.104	−0.675	−0.681	−0.896
Kurtosis	13.969	13.789	10.440	6.274	6.302	4.731
VaR	−0.661	−0.661	−0.694	−0.910	−0.910	−0.986
mVaR	−1.323	−1.323	−1.107	−1.275	−1.275	−1.117

A comparison between the portfolios with the different Asian indexes shows that ASEAN portfolios have less variance and VaR than their non-ASEAN peers. This clearly indicates that less developed ASEAN markets serve as better hedges for Brent oil when the targets are Var and VaR. This is to be expected because the ASEAN indexes have less variance than the non-ASEAN indexes and lower equicorrelation. Our results are in line with the papers by Mensi et al. (2021) and Abuaf et al. (2018). The former researched volatility spillover and portfolio construction between seven developed markets, five BRICS markets, and two strategic commodity futures markets (oil and gold). They reported that hedging effectiveness is more pronounced in BRICS markets than in developed markets. Abuaf et al. (2018) contends that countries whose stock markets have low correlations to that of the United States provide better diversification for US investors. They reported that Mexico and China appear to be the most important diversifiers.

But we cannot assume, based on the preliminary findings, that the non-ASEAN mVaR portfolio has lower mVaR, although these indexes have lower kurtosis. This is because the non-ASEAN indexes have higher equicorrelation and higher standard deviation, which is important factors in mVaR calculation. As it turns out, the doubt was justified because the ASEAN mVaR portfolio has slightly lower modified downside

Table 6
Weights calculated for selected assets in the two portfolios with Brent restrictions.

	Portfolios with ASEAN indexes				Portfolios with non-ASEAN indexes		
	Var	VaR	mVaR		Var	VaR	mVaR
Brent oil	50%	50%	50%	Brent oil	50%	50%	50%
IDX	5%	5%	0%	CSI1000	10%	10%	42%
KLSE	44%	44%	50%	Hang Seng	0%	0%	0%
FTWISGPL	0%	0%	0%	NIKKEI225	0%	0%	0%
SET	0%	0%	0%	KOSPI	36%	36%	8%
PSEi	1%	1%	0%	TPEX50	4%	4%	0%
Σ	100%	100%	100%	Σ	100%	100%	100%

Table 8
Descriptive statistics of the portfolios created with Brent constraints.

	Portfolios with ASEAN indexes			Portfolios with non-ASEAN indexes		
	Var	VaR	mVaR	Var	VaR	mVaR
Mean	0.019	0.019	0.020	0.011	0.011	0.002
Variance	0.390	0.390	0.390	0.384	0.384	0.434
Skewness	−1.779	−1.779	−1.732	−2.396	−2.396	−1.924
Kurtosis	24.875	24.875	24.353	22.585	22.585	17.007
VaR	−1.432	−1.432	−1.434	−1.429	−1.429	−1.532
mVaR	−3.703	−3.703	−3.685	−2.599	−2.599	−2.532

risk (−1.107) than the non-ASEAN portfolio (−1.117) in Table 7, although the non-ASEAN portfolio has lower kurtosis. However, the non-ASEAN portfolio has higher variance and higher equicorrelation, which play a decisive role in explaining its higher mVaR risk, despite the lower kurtosis.

Table 8 shows the descriptive statistics of the portfolios created with Brent constraints. The portfolios with the ASEAN indexes are higher in all three risks than the non-ASEAN portfolios. This is unexpected and quite the opposite of the optimal minimum-risk portfolios in Table 7. The rational explanation of these results is that oil has a very low share (1%, 1%, and 1%) in the optimal minimum-risk ASEAN portfolios, while it is somewhat higher (7%, 7% and 6%) in the non-ASEAN portfolios. As the share of oil in the portfolio increases, so does the risk of such a portfolio, and this is more evident in the portfolio with a lower share of oil, that is, the ASEAN portfolio. This is why more developed non-ASEAN indexes are more suitable for Brent hedging when investors hold more oil in a portfolio, although these indexes are more correlated.

Table 9 presents the results of the portfolios created, using hedge effectiveness indexes. Panel A shows that the Var, VaR, and mVaR of Brent fall 93.9 percent, 75.1 percent, and 83.6 percent, respectively, when Brent is combined with ASEAN indexes. This is higher than with the portfolios of the non-ASEAN indexes (87.2%, 64.1%, and 78.5%). The reasons are lower variance of the ASEAN indexes and their lower integration. However, when the constraint is imposed on Brent in the portfolios, then the non-ASEAN indexes are slightly better risk hedgers in the min-Var and min-VaR portfolios, and significantly better in the min-mVaR portfolio (see Panel B of Table 9). These results have two explanations. The first is a higher percentage of Brent in the optimal portfolios with non-ASEAN indexes, and the second one has significantly lower kurtosis of the non-ASEAN indexes vis-à-vis the ASEAN peers (see Table 1).

8. Conclusion

This paper tries to hedge Brent oil with respect to three different risk measures (variance, value-at-risk, and modified value-at-risk), combining it with two groups of East Asian indexes: ASEAN and non-ASEAN. As a preliminary indicator, we calculate equicorrelation with the DECO-DCC model, whereas multivariate portfolios are constructed using three different portfolio optimization procedures (VaR, VaR, and mVaR).

We have several noteworthy findings to report. First, the preliminary results reveal that the emerging ASEAN indexes have lower equicorrelation than the more developed non-ASEAN indexes. Moreover, the ASEAN indexes have lower variance and value-at-risk because they have less trading volume than their non-ASEAN counterparts. However, lower trading volume is responsible for the higher kurtosis of the ASEAN indexes, which means that these indexes have higher extreme risk, that is, modified downside risk.

The optimal minimum-risk portfolios created show that the ASEAN indexes are better hedges for Brent in terms of minimum variance and minimum value-at-risk. Although the ASEAN indexes have higher extreme risk, we find that a portfolio with these indexes actually has slightly lower mVaR than the portfolio with the non-ASEAN indexes. The reason is probably the higher variance and higher equicorrelation of the non-ASEAN portfolio, because these inputs affect the value of modified downside risk. In the optimal minimum-risk portfolios, the portfolio optimization procedures reduce the share of oil to a very low value (1%, 1%, and 1%) in the combination with the ASEAN indexes, and slightly higher (7%, 7%, and 6%) in the combination with the non-ASEAN indexes. However, when we put a 50 percent constraint on Brent in the portfolios, the portfolios with the non-ASEAN indexes have better risk-minimizing results. This happens because a higher share of Brent in the portfolio has a more adverse effect in situations in which the optimal share of oil is lower, and vice-versa, and this is the case in the portfolio with the ASEAN indexes.

We think that the results from this paper might be valuable for oil producers, traders, or investors from East Asia. The

Table 9
Calculated HEI values of the portfolios created with and without oil constraints.

	Portfolios with ASEAN indexes			Portfolios with non-ASEAN indexes		
Panel A. Portfolios without Brent constraints						
Hedge effectiveness indexes	HEI (Var)	HEI (VaR)	HEI (mVaR)	HEI (Var)	HEI (VaR)	HEI (mVaR)
	0.939	0.751	0.836	0.872	0.641	0.785
Panel B. Portfolios with Brent constraints						
Hedge effectiveness indexes	HEI (Var)	HEI (VaR)	HEI (mVaR)	HEI (Var)	HEI (VaR)	HEI (mVaR)
	0.715	0.466	0.458	0.719	0.468	0.628

results clearly indicate how the portfolios should be constructed when market participants have different risk-minimizing goals. The findings unequivocally suggest that the ASEAN indexes offer better oil hedging. However, when an investor holds more oil in a portfolio, then a combination with the non-ASEAN indexes gives a better risk-minimizing outcome. We also recommend the use of more elaborate mVaR portfolio optimization with respect to inferior Var and VaR procedures, in which portfolio construction is determined based on all four moments of the portfolio distribution.

Declaration of competing interest

The authors report no conflict of interest.

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