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RESEARCH ARTICLE

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Investment opportunities in the energy market: What can be learnt from different energy sectors

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Abstract

We construct portfolio strategies consisting of different stocks from four main energy market sectors, including oil and gas, oil and gas related equipment and services, multiline utilities and renewable energy. To construct portfolio strategies, we first forecast assets' returns by using multivariate copula models. These forecasting frameworks enable us to undertake both symmetric and asymmetric tail connectedness in simulating from the joint distribution. Second, we applied four major risk measures including volatility, mean absolute deviation, conditional value-at-risk and conditional drawdown-at-Risk. Our findings indicate that the consideration of homogeneity of oil and gas sector and oil and gas related equipment and services sector, together with the heterogeneity of multiline utilities sector and renewable energy sector should lead to information decoupling among these sectors, thereby providing portfolio diversification. The mixed copula model results in better out-of-sample economic performance, indicating the advantage obtained from modelling both symmetric and asymmetric tail dependence. Our analysis of the portfolio weights, among the energy market sectors, shows that for optimal portfolios, multiline utilities and renewable energy sectors constitute higher portion of the invested assets. The study results provide an encouraging guideline for developing renewable energy sector from the perspective of financial market.

KEYWORDS

energy sector, oil and gas firms, portfolio optimization, renewables, tail dependence, vine copulas

1 | INTRODUCTION

Over the recent years, large organizations with highly concentrated operations and services within oil & gas sector encounter relentless pressure in substituting their dependence on depleting natural resources, reducing CO_2 emissions (Rogelj et al., 2016; UNFCC, 2015; United Nations, 2018), and in generating profit-oriented operations to increase the shareholder value. The rapid technological advancements and geopolitical upheaval have contributed to significant alteration in oil and gas activities across the globe. Furthermore, the impact of such advancements is significantly higher for the larger producers as they need to amend and replace their existing practises towards more sustainable short- and long-term operations. Above that, the environment sustainability issues surrounding the oil and gas firms generate uncertainty for the market participants causing an increase shift in investment from traditional energy sector to renewables.

Consequently, a large number of oil and gas producers has started to invest in the clean energy and renewable sector (Chaiyapa et al., 2018; Mäkitie et al., 2019; Steen & Weaver, 2017; Zhong & Bazilian, 2018). For example, total SA pledges an yearly investment of $500 million in renewable energy (Blas, 2015), Equinor establishes an in-house venture capital fund to invest $200 million in renewable energy (Equinor, 2019), and Shell pledges to invest between $1 and $2 billion annually in renewable energy over the period from 2016 to 2020 through its New Energies division (Shell, 2019). In addition, the business cycle impacting the oil and gas sector, oil and gas related equipment and services, and multiline utilities is significantly different from the renewable energy sector. The high reliance of oil and gas sector on the fossil fuels largely impacts their long-term sustainable operations due to continuous depletion of available resources. On the contrary, the renewables are primarily dependent on unlimited natural resources, resulting in both short- and long-term sustainability of their operations.

Renewable energy sector has received considerable attention worldwide as a sustainable alternative to traditional energy sources due to various reasons, for instance depletion of fossil fuels, growing concern surrounding climate change, technological revolution, energy security issues, and uncertain prices of crude oil (Ferrer et al., 2018). Over the last decade, the renewable energy sector has experienced an exponential growth with global investment in renewable energy capacity hitting $272.9 billion (excluding large hydro-electric projects) in 2018, totalling $2.6 trillion. In terms of individual subsector, solar has attracted $1.3 trillion, wind secured $1 trillion, and biomass and waste-to-energy $115 billion (McCrone et al., 2018; McCrone et al., 2019). Figure 1 provides an overview of the historical development of new investments across various renewable sources. Climate risk and the energy security issues have surfaced as the primary factors in transforming the landscape of global energy sector towards clean and renewable energy (Grandell et al., 2016). In addition, the recent unfavourable situation with Iran, Libya and other Gulf countries (Iraq, Qatar) result in uncertain crude oil prices, thereby further favouring the shift from traditional energy sector to the renewable sources of energy.

The firms operating in traditional energy-related sectors behave homogeneously and are largely influenced by the variations in the crude oil price. Specifically, the crude oil price uncertainty determines the futures operations of these firms regarding investment in new plants, exploration activities, demand shocks and supply disruptions, among others, thereby influencing the stock prices and the investment allocation decisions.

In this regard, the business cycle linkage for the three traditional energy sectors is completely different from the renewables sector. Furthermore, the traditional energy sector primarily relies on the depleting fossil-fuel, while the renewables sector depends on unlimited supply of natural resources (solar, wind, hydropower, geothermal) to produce energy. Given these circumstances, the market participants may accomplish portfolio diversification and risk management by allocating their investment in

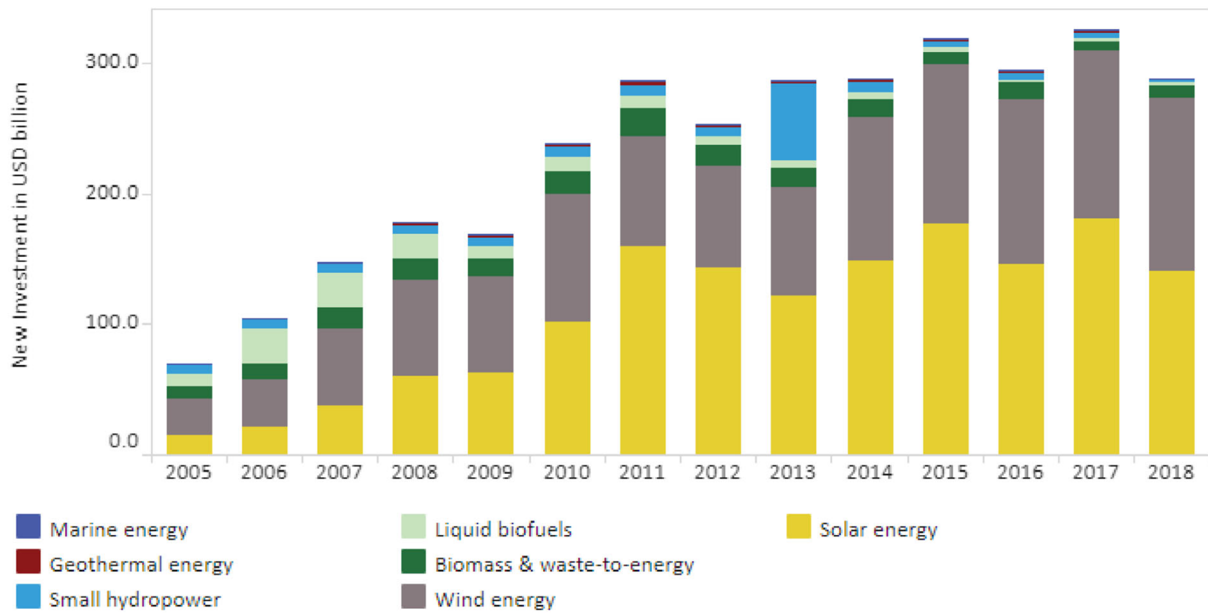

FIGURE 1 New investment in various renewables (IRENA, 2018) [Colour figure can be viewed at wileyonlinelibrary.com]

the firms operating in the three traditional energy sectors, as well as the renewables sector.

For the above-mentioned concerns, understanding the connectedness dynamics among the assets becomes significant importance for both academics and market participants that are investigating the behaviour of financial and commodity markets. With the outbreak of the global financial crisis of 2008 (GFC), the portfolio diversification, dynamic hedging, and risk management potential of investing between financial and commodity markets has weakened (Elie et al., 2019; Rehman et al., 2019; Uddin et al., 2019). Therefore, both academics and practitioners have dedicated significant attention in exploring other assets that may assist in portfolio diversification and risk management. In this study, the role of renewable will be investigated.

The connectedness dynamics and safe-haven properties of crude oil with various assets is widely studied in the existing literature (Al Janabi et al., 2017; Baffes, 2007; Dutta et al., 2018; Huang et al., 2016; Ji & Fan, 2012; Kang et al., 2017; Koirala et al., 2015; Manera et al., 2013; Mishra et al., 2019; Moreno et al., 2019; Pal & Mitra, 2017; Pandey & Vipul, 2018; Shahzad et al., 2017; Silva et al., 2017; Silvennoinen & Thorp, 2016; Yahya et al., 2019; Zhang & Chen, 2018). Similarly, numerous studies examine the relationship between crude oil and clean energy indexes (Dutta, 2017; Elie et al., 2019; Ferrer et al., 2018; Maghyereh et al., 2019; Troster et al., 2018; Uddin et al., 2019). Although several studies examine the portfolio management and safe-haven properties of energy sector (fossil-fuels and renewables), assessment of firm-level portfolio diversification and risk management benefits using oil and gas sector, oil and gas related equipment and services sector, multiline utilities sector, the renewables sector has received less attention.

Our study addresses these knowledge gaps by evaluating the multi-asset portfolio diversification and risk management potential between four energy sectors, namely oil and gas sector, oil and gas related equipment and services sector, multiline utilities sector, and the renewables sector by utilizing various symmetric and asymmetric copula frameworks. The existing literature primarily revolves around examining the connectedness dynamics between energy sector with other asset classes. However, despite heterogeneous operations and nature of firms operating across oil and gas sector, oil and gas related equipment and services sector, multiline utilities sector, and renewables sector, the interconnectedness and portfolio diversification potential between these firms remains uncharted.

This article fills the pivotal rift in several ways. First, to the best of our knowledge, this is the first empirical paper examining the relationship among the above-mentioned four sectors by utilizing firm-level data. Several studies examine the relationship of energy sector with the renewables, nevertheless, these studies primarily focus on the aggregate level or sectorial indices. Surprisingly, relatively few studies examine the firm-level relationship of energy sector (see e.g., Antonakakis et al., 2018; Bondia et al., 2016; Gupta, 2016; Henriques & Sadorsky, 2008; Kocaarslan & Soytas, 2019; Madaleno & Pereira, 2015, among others). However, the above studies examine the firm-level relationship with the limitation only within oil and gas sector, or focusing on clean energy firms and crude oil. It is crucial to emphasize that the aggregate price data of crude oil might be insufficient to capture the heterogeneous nature of the firms operating across these sectors.

Second, unlike previous studies, we evaluate the multivariate firm-level portfolio diversification potential by utilizing data of firms operating across four energy sectors. The business cycle encircling these sectors are distinct due to energy sources, storage capacity, supply and demand interactions. Furthermore, each firm operating in these sectors has a broad set of operations and services. Therefore, the firm-level data from these sectors may allow us to unveil the potential diversification benefits due to heterogeneity of firms operating within these sectors.

Third, in contrast with the literature, we utilized various symmetric and asymmetric copula frameworks to estimate multivariate portfolio weights. Copulas, in general, are preferable over conventional correlations and multivariate GARCH models to capture the dependence during periods of prosperity and extreme market conditions. This is due to their capability in modelling, in particular, non-parametric and asymmetric tail dependence that has applications in risk management and portfolio downside risk optimization. The asymmetric properties of the financial and commodity markets are well documented in the literature (Elie et al., 2019; Uddin et al., 2019). Therefore, the asymmetric copula frameworks will allow us to capture the connectedness structure both in the mean and tails of the distributions. In addition, previous studies primarily provide an estimate of portfolio weights and hedge ratios in the bivariate scenario. However, we emphasize that the bivariate analysis neglects important information that may suffice for portfolio managers and investors in energy sectors who tend to include various firms in their investment choices. Therefore, the combination of asymmetric copula frameworks with multivariate portfolio diversification and risk management decisions may provide a broader and comprehensive perspective to the market participants regarding firm-level investment within energy sectors.

Our empirical analysis indicates a strong potential to attain diversification and risk management benefits by utilizing disaggregated-level data from the four energy sectors. Specifically, the heterogeneity of business cycle surrounding these sectors decouples the connectedness structure among the firms operating within, thereby leading to lower dependence among the assets. Our findings indicate existence of both symmetric and asymmetric tail dependence among the assets, favouring the utilization of copula-based frameworks to model interconnectedness. In terms of connectedness, we find Total (oil and gas sector) and Eni (oil and gas sector) provide the highest level of dependence, while PetroChina (oil and gas sector) and Shanghai Aerospace Automobile Electromechanical (renewable energy sector) provide the lowest level of dependence. In terms of out-of-sample portfolio performance, our findings indicate that the copula-based portfolios significantly outperform the benchmark portfolios. Regarding risk-adjusted performance, we find that the copula families which are sensitive to asymmetric tail dependence provide better avenue to reduce the downside risks of the energy stocks. The increased out-of-sample risk-adjusted performance is attributed to the addition of stocks from multiline utilities sector and renewables sector together with stocks from oil and gas sector and oil and gas related equipment and services sector that improves the out-of-sample risk-adjusted performance of the overall portfolio. Whereas, in terms of Sharpe ratio, the optimal portfolios from mixed copula outperform other copula families. In terms of out-of-sample economic performance, the benchmark portfolios are unable to increase the economic performance. However, using copula-based forecasting models, the optimal portfolios outperform the mean-risk strategies. In terms of out-of-sample portfolio weights, our findings indicate a higher proportion of wealth to be allocated in multiline utilities sector and renewable energy sector to attain portfolio diversification and risk management benefits.

The empirical findings reported in this research are of significant interest to policymakers, institutional investors, portfolio managers, and international investors. The asymmetric dynamic connectedness structure among assets necessitates the policymakers to develop policies that decouple the information connectedness and facilitate in smooth transition from traditional energy sources to renewables. In regard to institutional investors and portfolio managers, our findings indicate that an assessment of time-varying symmetric and asymmetric tail-dependence and connectedness dynamics is crucial in devising and implementing portfolio allocation and risk management decisions concerning investment in oil and gas sector, oil and gas related services sector, multiline utilities sector, and renewable energy sector. Furthermore, our findings suggest that the portfolio managers and investors may utilize various active risk minimization and optimal portfolio allocation strategies to attain out-of-sample diversification and risk management benefits.

The rest of the article is structured as follows. Section 2 presents the stylized facts surrounding the energy markets and an overview of employed data. Section 3 presents the employed methodological framework. Section 4 presents the empirical findings. Section 5 concludes the study.

2 | STYLIZED FACTS AND DATA

In this section, we first present the stylized facts surrounding the energy market. Second, we provide an overview of the employed data along with stochastic properties.

2.1 | Stylized facts of energy markets

The prices of oil underwent a significant decline during 2014–2016. For instance, the per barrel price of WTI crude oil declined by around 80% ($106.46 on 27th June 2014 to $26.21 on 11th February 2016). Crude oil has been widely acknowledged as the most influential commodity due to its importance towards economic development and prosperity. An increase in crude oil price leads to an increase in the production cost of goods and services, transportation cost, induce uncertainty, increase inflation and negative impact on economic growth, among others. Whereas a decline in crude oil price significantly impacts the firms operating across oil and gas sector, oil and gas related equipment and services sector, and multiline utilities sector primarily due to high dependence and reliance on crude oil price. It may impact the firms operating beyond these sectors; however, evaluation of its impact outside the aforementioned sectors is beyond the scope of this study.

Given their high reliance on crude oil, the interconnectedness between crude oil and the firms operating in oil and gas sector is indisputable. The firms operating in this sector are largely engaged with upstream (exploration and production) and downstream activities (refinement of crude oil and natural gas). The stock prices of the firms operating in this sector are highly sensitive to the variations in the crude oil prices. For instance, the stock price of ConocoPhillips declined by 60% ($73.68 on 27th June 2014 to $29.44 on 11th February 2016). In addition, the stock price of ConocoPhillips increased ($29.44 on 11th February 2016 to $76.53 on 3rd October 2018) with the rise in crude oil price ($26.21 on 11th February 2016 to $76.41 on 3rd October 2018). Similar trend is observed for other firms operating in the oil and gas sector, for instance Eni ($38.57 to $19.43 and from $19.43 to $35.59) and PetroChina ($108.07 to $50.56 and from $50.56 to $78.45). This indicates the high reliance of these firms on the crude oil prices to maintain their current and prospective exploration activities.

In regard to the firms operating in oil and gas related equipment and services sector, their operational activities are highly dependent on the exploration and production activities of the oil and gas sector. The firms in this sector may be characterized as midstream (pipeline, oil tankers, among others) as they assist the oil and gas sector by providing specialized equipment and services. Similar to the oil and gas sector, the operations of oil and gas related equipment and services sector is highly dependent on the crude oil price. For instance, Halliburton stock price fell from $63.45 (2014) to $26.56 (2016) and increased from $26.56 (2016) to $40.35 (2018) with the decline and incline of crude oil price, respectively. Similarly, the stock price of National Oilwell Varco has declined from $75.41 to $25.39 and increased again to $44.25. The high dependence of oil and gas related equipment and services sector on the oil and gas sector may induce an increased connectedness structure among these two sectors.

The multiline utilities firms often offer a wide range of products and services to the oil and gas sector, oil and gas related equipment and services sector, and renewable energy sector. In addition, these firms provide a wide range of products and services to other businesses and consumer market, for instance telecom services, digital products, environmental services, among others. Therefore, the business cycle of these firms is heterogeneous from the oil and gas sector and oil and gas related products and services sector. Furthermore, these firms may instantaneously change their products and services to meet the growing demand from one sector to another. Therefore, their operations may not be significantly affected by the uncertainty in the crude oil prices. For instance, the stock price of Sempra exhibits no significant fluctuation ($89.28 on 27th June 2014 to $84.43 on 11th February 2016) due to oil price drop. However, the stock price does increase significantly during the post-2016 period to $111.22 on 3rd October 2018. Similarly, the price of PPL exhibited an upward price trend from $25.48 in 2014 to $29.90 in 2016 and remain relatively stable with the increase in crude oil price during post-2016 period. However, similar to firms in oil and gas sector and oil and gas related equipment and services sector, MDU Resources exhibited a downward trend with the decline in crude oil price from $29.29 in 2014 to $14.55 in 2016. Whereas, over the post-2016 period, the price of MDU Resources increases $24.78 on 3rd October 2018. This suggests that the firms in the multiline utilities are of heterogenous nature both within the sector and compared with oil and gas sector and oil and gas related products and services sector.

Renewable's sector has gained significant attention due to climate change and global warming. Climate uncertainty intensified by global warming is also manifesting its importance in the energy portfolio diversification towards de-carbonization. As per Renewables Information, the share of renewables and clean energy, which provided 24% of world's power demand in 2017, is estimated to increase by 30% by 2023 (Birol, 2018). An upsurge of investments in renewables to a level of $279.8 billion in 2017 results in cumulative investments in the sector to $2.6 trillion (McCrone et al., 2018) providing further thrust to the renewables in the global energy sector. Figure 2 provides an overview of the reference and REmap (global roadmap proposed by International Renewable Energy Agency [IRENA]) case electricity generation using renewables and non-renewables. Referring to REmap case, the dependence on non-renewables as energy source will significantly decline until 2050 (IRENA, 2018). Unlike oil and gas sector, the renewables rely on natural resources to produce energy, for instance wind, thermal, solar, among others. Therefore, the business cycle impacting the renewables are totally different from that of oil and gas sector, oil and gas related products and services sector, and multiline utilities. For instance, the share price of Siemens Gamesa Renewable Energy has increased by around 45% ($10.84 on 27th June 2014 to $15.52 on 11th February 2016) with the decrease in crude oil price. However, with the upsurge in crude oil price, the price has decreased by around 25% to $11.85. Similarly, Vestas Windsystems exhibited an increase of around 60% (DKK253.98 on 27th June 2014 to DKK 413.52 on 11th February 2016), while it remains stable at this level during the post-2016 period.

Overall, these observations suggest that the firms operating across oil and gas sector, oil and gas related equipment and services sector, multiline utilities sector and renewable sector are of heterogenous nature and characterize by different business cycles, indicating potential to attain portfolio diversification and risk management benefits by utilizing firm-level data from these sectors. This study attempts to confirms this, and in addition explore how to obtain such advantages.

2.2 | Data and stochastic properties

We employ daily stock price data of 28 firms operating across the four sectors. The sample period spans from 15th May 2003 to 23rd April 2019, resulting in 4158 trading days. The data utilized in this is collected from

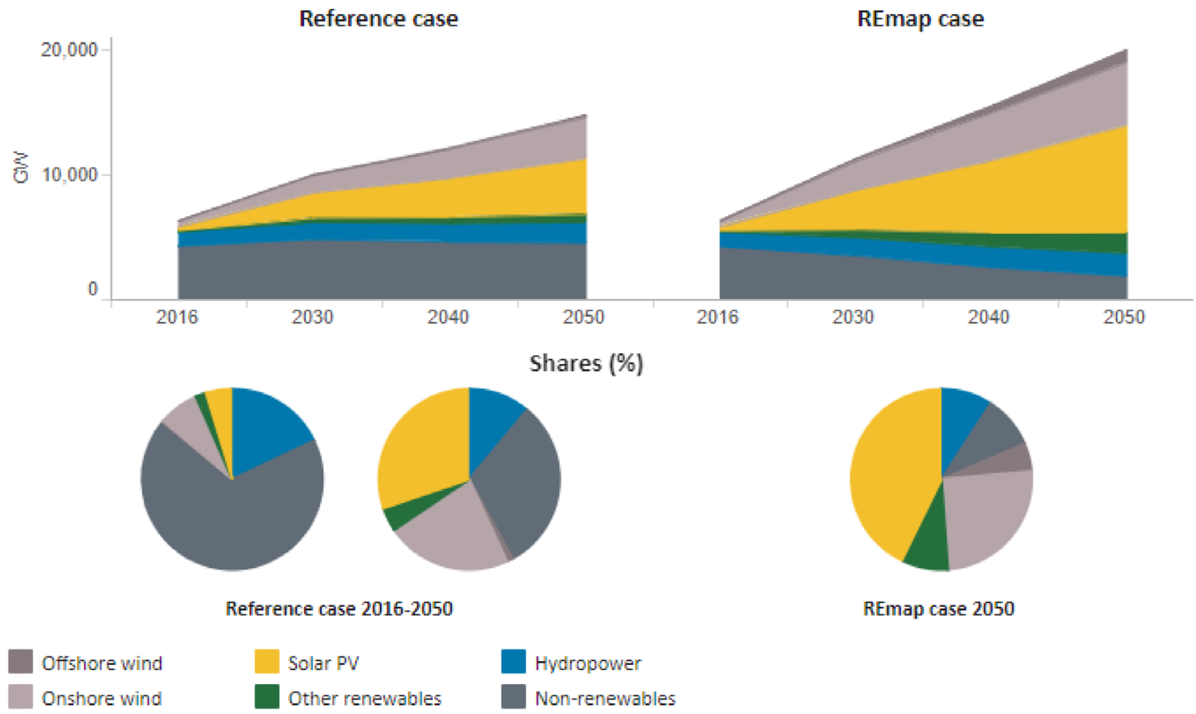

FIGURE 2 Development of electricity generation for various sectors. (IRENA, 2018) [Colour figure can be viewed at wileyonlinelibrary.com]

Thomson Reuters DataStream. The starting date is dictated primarily due to availability of the data. We choose the firms based on the following specifications and criterions. First, the confidence of the investors on the firm's management and its risk profile. This criterion is important as it safeguards the investors regarding liquidity of their investment. Second, the firm needs to be financially stable, that is the firm is not under financial distress. This complements the first criterion as investors deem to move away from the financially distressed firms. Third, the innovativeness of the firm that is the firm continue to invest in new technologies in order to increase the shareholder value. Based on these criterions, we select seven firms from each sector (Reuters, 2019).

Table 1 provides the descriptive statistics for daily logarithmic returns for each stock. All stocks are categorized based on four sectors (Panels A–D). Most of the stocks have positive average return, except for CGG, Weatherford International, E.ON SE, RWE, Pacific Ethanol and Solar World. The highest daily average return (0.063%) is reported for Vestas, while the lowest daily average return is reported by Solar World (−0.156%). In general, renewable energy sector shows higher volatility and lower returns compared to other sectors, while oil and gas sector and multiline utilities sector provide the lowest level of volatility. The highest volatility is reported for Pacific Ethanol (6.448%), while Sempra Energy shows the lowest volatility of 1.335%. Both minimum and maximum returns are reported for Solar World (−151.002% and 50.608%). Most of the firms in the sample exhibit negatively skewed and leptokurtic return distribution. Furthermore, these estimates suggest deviation from normal distribution. The results from Jarque-Bera normality test affirms this non-Gaussianity and strongly rejects the null-hypothesis of normality at the 1% threshold level, indicating fat tails characterize the distribution. The ARCH test (Engle, 1982) with one lag rejects the null-hypothesis of homoscedasticity at the 1% threshold level, indicating the existence of ARCH effects and volatility clustering for all series. This advocates the importance and relevance of GARCH-type framework to model the stylized facts of the underlying series. Furthermore, the Ljung-Box test with 10 lags is significant for most of the series, indicating rejection of null-hypothesis of independence.

3 | METHODOLOGY

We model the dependence structure among the assets by utilizing Rvine copula models to construct different portfolio strategies for the energy markets. We consider thresholded and truncated Rvine model, in which, based on a truncation level, the vine structure is reduced by setting the low-dependence copulas to an independence one. To capture and compare symmetric and asymmetric

TABLE 1 Descriptive statistics

Series	Mean	*SD*	Min	Max	Skewness	Kurtosis	JB	ARCH	Ljung-box
Panel A: Oil and gas									
ConocoPhillips	0.029	1.867	−14.869	15.365	−0.321	6.473	7341***	472***	44***
Eni	0.004	1.801	−12.386	19.113	0.282	11.086	21375***	87***	62***
ExxonMobil	0.021	1.421	−15.027	15.863	−0.013	14.365	35791***	430***	134***
Hess Corporation	0.035	2.502	−21.265	15.441	−0.607	8.032	11446***	211***	33***
PetroChina	0.025	2.215	−14.903	14.415	−0.027	5.817	5871***	222***	34***
Royal Dutch Shell	0.009	1.564	−10.78	15.631	0.115	9.258	14877***	277***	44***
Total	0.011	1.694	−11.597	15.756	0.131	7.834	10658***	263***	53***
Panel B: Oil and gas related equipment and services									
CGG	−0.062	3.693	−34.962	44.367	0.472	14.428	36263***	45***	28***
Halliburton	0.023	2.342	−18.758	21.147	−0.461	7.518	9953***	165***	20**
National Oilwell Varco	0.022	2.709	−24.068	21.852	−0.593	10.412	19048***	413***	45***
SBM Offshore	0.01	2.468	−28.287	18.838	−0.431	11.248	22074***	33***	17*
Schlumberger	0.016	2.075	−20.339	13.902	−0.489	8.665	13190***	137***	39***
TransCanada	0.024	1.339	−11.095	9.511	−0.37	6.18	6722***	348***	58***
Weatherford International	−0.069	3.552	−38.199	32.647	−0.618	14.766	38084***	118***	30***
Panel C: Multiline utilities									
E.ON SE	−0.01	1.986	−14.629	19.983	−0.31	8.723	13267***	195***	56***
EVN	0.007	1.611	−10.303	10.899	−0.008	4.024	2811***	117***	11
MVV Energie	0.013	1.608	−21.205	9.242	−0.527	10.377	18872***	92***	109***
MDU Resources Group	0.015	1.61	−13.668	21.399	−0.017	16.516	47311***	309***	53***
PPL	0.013	1.34	−14.138	13.802	−0.594	13.253	30710***	54***	55***
RWE	−0.004	2.032	−13.385	17.225	−0.079	6.504	7345***	128***	30***
Sempra Energy	0.039	1.335	−17.68	14.443	−0.303	20.484	72836***	128***	104***
Panel D: Renewable energy									
Motech Industries	0.016	3.02	−13.976	12.783	0.052	1.002	176***	93***	50***
Pacific Ethanol	−0.128	6.448	−58.045	50.349	0.734	11.897	24927***	210***	18*
Shanghai Aerospace Automobile Electromechanical	0.013	3.196	−12.26	10.697	−0.239	2.366	1011***	293***	42***
Siemens Gamesa Renewable Energy	0.023	2.79	−27.366	22.475	−0.182	8.181	11634***	22***	16
SolarWorld	−0.156	6.27	−151.002	50.608	−3.4	93.654	1529116***	70***	59***
Vestas	0.063	3.319	−29.43	22.217	−0.39	9.943	17254***	78***	22**
Xiangtan Electric Manufacturing	0.018	3.13	−26.236	11.507	−0.26	3.133	1750***	96***	16

Note: This table provides descriptive statistics for daily returns of 28 energy market stocks. For each stock, the total number of observations is 4158. The sample period is from 16 May 2003 to 23 April 2019. JB is the result of Jarque-Bera's normality test. The test statistic for Ljung Box Q (with 10 lag) and ARCH (with 1 lag) tests are reported. ***, **, * denotes significant at 1%, 5% and 10% level, respectively.

tail dependence, we examine different copula families, each of which is sensitive to lower, upper or both tails. Having modelled the tail dependence, we forecast the conditional distribution of assets and draw simulations from the joint distribution. Then, we optimize and evaluate the performance of portfolio strategies based on different risk measures. The portfolio optimization methods are provided in Appendix A.

3.1 | Truncated regular vine copula

According to Sklar (1959), for a d-dimensional joint distribution F, there exists a copula C with univariate marginal distributions $F_1, F_2, ..., F_d$ such that:

$$F(z_1, z_2, ..., z_d) = C(F_1(z_1), F_2(z_2), ..., F_d(z_d)) \\ = C(u_1, u_2, ..., u_d), \forall z \in \Re^d, \quad (1)$$

where, F is a multivariate distribution function, such that $z_n = F_n^{-1}(u_n),\ u_n \sim U[0,1]^d, \forall n \in \{1,2,...,d\}$. Joe (1996) introduced pair-copula construction (PCC) by using distribution functions. However, Bedford and Cooke (2002) derived graphical representation of PCC in forms of nested trees, including regular (Rvine), drawable (Dvine) and canonical (Cvine) structures (see Aas et al., 2009 for further information on statistical inference and estimation of vine copulas).

In a vine structure, there are in total $d-1$ trees and $d(d-1)/2$ bivariate copulas to be estimated. Therefore, increasing the number of assets leads to more complexity in estimating the vine structures. To overcome this problem, the vine structure could be simplified or truncated (see e.g., Brechmann et al., 2012; Nagler et al., 2019). One approach is to apply truncation to the number of trees in the vine. Let $I \in \{1,2,...,d-1\}$ be a specific tree from which all pair-wise copulas are set to independence copula. The intuition is that in a vine structure, final trees and edges generally do not show strong dependence, and therefore can be simplified. In this case, for a truncated regular vine copula, the density function is imposed as:

$$c^{Truncated}(\boldsymbol{u}) = \prod_{i=1}^{I} \prod_{e \in E_i} c_{j_e,k_e|D_e}\left(C_{j_e|D_e}\left(u_{j_e}|\boldsymbol{u}_{D_e}\right), C_{k_e|D_e}\left(u_{k_e}|\boldsymbol{u}_{D_e}\right)\right). \quad (2)$$

While the simplification in truncated Rvine copula is for the number of trees, the thresholded Rvine sets the *irrelevant* pair-copulas to independence. Let τ_e be the Kendall's τ for the conditional pair-copula $c_{j_e,k_e|D_e}$, by setting $E_i^0 = \left\{e \in E_i \middle| |\tau_e| > \acute{\theta}\right\}$ for each edge set E_i, the density of a thresholded Rvine is:

$$c^{Thresholded}(\boldsymbol{u}) = \prod_{i=1}^{d-1} \prod_{e \in E_i^0} c_{j_e,k_e|D_e}\left(C_{j_e|D_e}\left(u_{j_e}|\boldsymbol{u}_{D_e}\right), C_{k_e|D_e}\left(u_{k_e}|\boldsymbol{u}_{D_e}\right)\right). \quad (3)$$

3.2 | One-step ahead forecasting

Based on the descriptive statistics reported in Table 1, all the underlying return series exhibit autocorrelation and ARCH effects, thereby favouring the utilization of a mean-type framework together with GARCH-types of modelling approach. Therefore, we utilize an AR(1)-GARCH(1, 1) specification to capture the stylized facts embedded in the return series, which may be specified as:

$$\begin{cases} \mathrm{r}_{nt} = \mu_n + \gamma_n \mathrm{r}_{n,t-1} + \varepsilon_{nt} \\ \varepsilon_{nt} = z_{nt}\sigma_{nt},\ z_{nt} \approx STD(0,1,\xi_n)\ . \\ \sigma_{nt}^2 = \omega_n + \alpha_n \varepsilon_{n,t-1}^2 + \beta_n \sigma_{n,t-1}^2 \end{cases} \quad (4)$$

We utilize a simulation-based approach to construct portfolio strategies. In the first step, we utilize the AR(1)-GARCH(1, 1) specification to forecast one-step ahead conditional mean $\widetilde{\mu}_{nt}$ and volatility $\widetilde{\sigma}_{nt}$ and estimate the standardized residuals $\boldsymbol{z}$. Then, pseudo-observations $\boldsymbol{u}$ are obtained from probability function of marginal distribution of the standardized residuals. Following that, we estimate the parameters for truncated and thresholded copulas in Equations (2) and (3). Based on the copula parameters and the estimated joint distribution, we apply the inverse function of marginal distribution to obtain simulated standardized residuals $\widetilde{\boldsymbol{z}}$. Finally, one-step ahead simulated returns are estimated as:

$$\forall m \in \{1,2,...,M\}: \widetilde{r}_{nt}^m = \widetilde{\mu}_{nt} + \widetilde{\sigma}_{nt}\widetilde{z}_{nt}^m, \quad (5)$$

where, $t = 1,2,...,T$ is the out-of-sample iteration.

4 | EMPIRICAL ANALYSIS

We examine the portfolio diversification potential of investment allocation across oil and gas, oil and gas related equipment and services, multiline utilities, and the renewables sectors. To do so, we focus on firm-level data of 28 top leading firms from these sectors based on the ranking approach proposed in the methodology section. The heterogeneity nature of operations and services of these sectors may allow us to attain diversification benefits by allocating portfolio weights across these sectors. In particular, the oil and gas sector and oil and gas related services sector behave rather homogeneously, while the multiline utilities sector and the renewables sector behave heterogeneously from the prior two sectors. Furthermore, the business cycles characterizing the operations of these sectors are significantly different across all the four sectors. Therefore, we propose that the institutional investors and portfolio managers may attain diversification benefits by utilizing the firm-level data of multiline utilities and renewables sectors together with the traditional oil and gas sector. The investigation may provide us with an understanding of each sector's performance in a multidimensional portfolio setting. For doing so, we first perform in-sample investigation, in which we look at (1) properties and results of conditional mean and conditional volatility modelling, and (2) tail dependence between assets. Second, we use out-of-sample back-testing to analyse and compare the properties of each portfolio strategy and role of multiline utilities sector and renewables sector in providing diversification benefits. Finally, as the robustness check, we evaluate the performance of each portfolio in a multi-period setting.

4.1 | GARCH estimation

Table 2 presents the results of marginal distribution model over the whole sample period. We utilize AR(1)-GARCH(1, 1) specification to estimate the standardized

TABLE 2 Marginal distribution parameter estimation

	μ	γ	ω	α	β	ξ
Panel A: Oil and gas						
ConocoPhillips	0.089***	−0.023	0.027***	0.070***	0.923***	7.833***
Eni	0.065***	−0.038**	0.029***	0.062***	0.929***	6.569***
ExxonMobil	0.049***	−0.054***	0.023***	0.070***	0.919***	5.963***
Hess Corporation	0.092***	−0.002	0.030***	0.058***	0.938***	7.272***
PetroChina	0.031	−0.028*	0.039***	0.065***	0.928***	6.621***
Royal Dutch Shell	0.056***	0.026*	0.016**	0.055***	0.938***	6.370***
Total	0.066***	−0.028*	0.024**	0.056***	0.935***	7.781***
Panel B: Oil and gas related equipment and services						
CGG	0.016	0.056***	0.323***	0.100***	0.880***	4.366***
Halliburton	0.073**	0.025	0.057***	0.053***	0.935***	7.160***
National Oilwell Varco	0.065**	−0.006	0.019**	0.042***	0.956***	6.206***
SBM Offshore	0.073***	−0.002	0.057***	0.042***	0.949***	3.999***
Schlumberger	0.031	−0.016	0.017***	0.040***	0.956***	6.738***
TransCanada	0.048***	0.018	0.032***	0.059***	0.921***	7.238***
Weatherford International	0.064*	0.032**	0.070***	0.056***	0.937***	5.692***
Panel C: Multiline utilities						
E.ON SE	0.045**	−0.005	0.057**	0.060***	0.924***	5.413***
EVN	0.025	−0.034**	0.032***	0.065***	0.925***	5.168***
MVV Energy	0.030**	−0.167***	0.182***	0.121***	0.816***	4.282***
MDU Resources Group	0.058***	−0.027**	0.025***	0.048***	0.940***	5.395***
PPL	0.052***	−0.012	0.019**	0.051***	0.936***	5.832***
RWE	0.052**	0.029*	0.063*	0.054***	0.929***	5.237***
Sempra Energy	0.070***	−0.029*	0.048***	0.081***	0.887***	5.323***
Panel D: Renewable energy						
Motech Industries	−0.034	0.014	0.097	0.072***	0.927***	4.331***
Pacific Ethanol	−0.263***	−0.020	2.535***	0.261***	0.738***	3.222***
Shanghai Aerospace Automobile Electromechanical	0.000	0.005	0.000	0.115***	0.884***	4.216***
Siemens Gamesa Renewable Energy	0.090***	0.012	0.086***	0.075***	0.917***	4.723***
SolarWorld	−0.083*	−0.026	3.495***	0.468***	0.531***	3.229***
Vestas	0.088***	−0.017	0.124	0.062**	0.933***	3.549***
Xiangtan Electric Manufacturing	0.025	−0.015	0.188**	0.082***	0.917***	3.324***

Note: This table provides estimated parameters for AR-GARCH marginal modelling for daily returns of 28 energy market stocks. For each stock, the total number of observations is 4158. The sample period is from 16 May 2003 to 23 April 2019. μ and γ are the constant term and AR(1) coefficient the mean equation. ω, α and β are the GARCH (1, 1) parameters. ξ is the shape parameter for Student-*t* distribution. ***, **, * denotes significant at 1%, 5% and 10% level, respectively.

residuals. The lagged autoregressive parameter, γ, is significant at the 10% significance level in most of the cases in oil and gas and multiline utilities sectors, indicating that the past information is instantly diffused in current returns. The ARCH and GARCH components, α and β, are significant at the 1% significance level, indicating that the current conditional volatility is impacted by the lagged squared shocks and persistence in conditional volatility for all series. In general, the significance of estimated parameters in volatility equation suggests a standard GARCH model can properly model the conditional volatilities for all firm-level data. The parameter capturing the movements in the tails of the distribution, ξ, is strongly significant at the 1% significance level with values higher than 3, indicating the importance of utilizing Student-t to capture the potential co-movements in the tails. The tail-dependence suggests that the standard means-based models are not suitable to capture the stylized facts embedded in the energy markets. Furthermore, this indicates that an increase co-movement between these assets with other assets are highly likely during periods of financial and economic turmoil.

4.2 | Dependency structure

Based on the standardized residuals from the marginal distribution frameworks, we estimate the dependence structure between the 28 firms from all four sectors. Specifically, we utilize various copula families in this article to estimate the dependence structure including Student-t, Clayton, Joe, Frank, and a mixed version selected by applying mBICV criterion (see Nagler et al., 2019 for further information on the modified BIC selection criterion). In this section, we present the results for the truncate and threshold mixed Rvine copula.

Figure 3 plots the tree structure of the obtained estimates from the mixed Rvine copula. This figure only plots the first tree in the vine structure. To estimate the dependency structure, we first rank the stocks based on the sum of their correlations with other firms in the sample. This puts more correlated stocks in the centered nodes that have more dependence, showed in edges, with other stocks. In terms of simple correlation, we find that Total and Xiangtan Electric Manufacturing exhibits the highest and lowest degrees of connectedness with other firms in the portfolio, and therefore placed in the first and last nodes, respectively. As we can see in the figure, there are 28 nodes representing each stock and 27 edges representing pair-wise copulas. Each bivariate copula is selected based on mBICV criterion (panel A). To compare the dependency between assets, we use Kendall's tau estimated from pair-wise copulas in panel B.

According to panel A, in most cases, Student-t copula is selected as the pair-wise copula based on the mBICV criterion. This is primarily due to the conditional distribution in the AR-GARCH framework in which we model the errors distribution by utilizing Student-t. The joint multidimensional distribution constructed using this copula family belongs to symmetric multivariate distributions. This indicates, for instance between Total and RWE, there is symmetric tail-dependence. However, in some of the cases, Clayton and Frank copula families are selected based on mBICV. This indicates the existence of

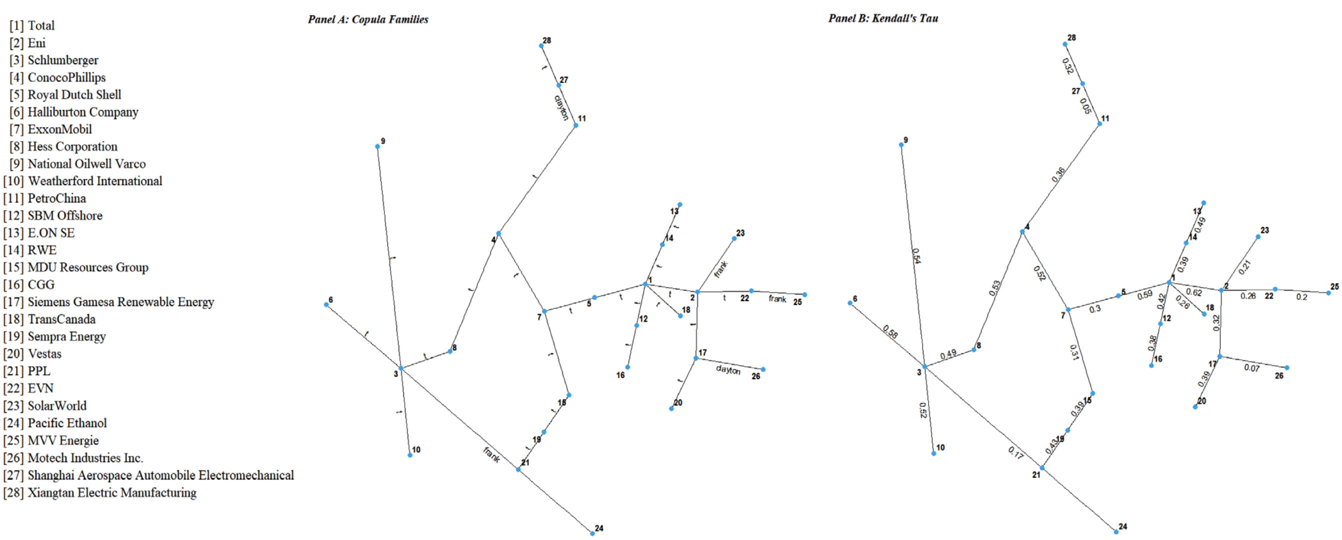

FIGURE 3 Dependency structure between 28 energy stocks. This figure illustrates selected copula families (panel A) and estimated Kendall's taus (panel B) from the truncated mixed Rvine copula model for daily returns of 28 energy market stocks. For each stock, the total number of observations is 4158. The sample period is from 16 May 2003 to 23 April 2019. Numbers at nodes represent the stocks [Colour figure can be viewed at wileyonlinelibrary.com]

both symmetric and asymmetric tail-dependence between the assets.

From Panel B, the highest Kendall's tau ($\tau = 0.62$) is reported between Total (node 1) and Eni (node 2), which belong to oil and gas energy sector. This is expected as the firms operating in the oil and gas sector are homogenous and tends to have same business cycle. In general, the most dependencies are reported within oil and gas and oil and gas related equipment and services sectors. There are also symmetric tail-dependence suggested for firms from different sectors. For instance, a Kendall's tau of 0.31 is reported between Exxon Mobil and MDU Resources Group. This indicates, despite of different operations, firms from different sectors have also dependency. On the other hand, the lowest Kendall's tau ($\tau = 0.05$) is estimated between PetroChina and Shanghai Aerospace Automobile Electromechanical, by using Clayton family. This reflect the heterogenous nature of the operations and services of the firms operating across oil and gas sector and the renewables. It is noteworthy that the firms in renewable sector exhibits relatively weak dependence with firms in the other three sectors. In particular, based on the in-sample analysis, these firms have dependencies with firms from oil and gas sector. However, these results are based on only first tree in the vine structure. When applying rolling window estimation, the dependency structure changes over the out-of-sample period. This indicate that the dependence dynamics among the assets varies over time and thereby necessitates the institutional investors and portfolio managers to recursively estimate the employed framework with the additional observation in the estimation window.

4.3 | Portfolio back-testing

Based on the dependence structure between assets estimated using simplified Rvine copula model, we simulate from the joint distribution and obtain one-step ahead simulated assets' returns, $\widetilde{\boldsymbol{r}}_t$, using a rolling window estimation of the forecasting models. We use the estimation window of 1000 days. The empirical output from various rolling window lengths, such as $T = 500; 750; 1250; 1500$, are qualitatively similar; thus, for brevity, we only report for the case of 1000 days. Based on the derived one-day-ahead returns, we compute the portfolio weights, $\boldsymbol{w}_t$, for each copula family based on eight different portfolio strategies from two general methods, namely minimum variance (Mean–variance, Mean-CVaR, Mean-MAD and Mean-CDaR) and maximized returns (optimal portfolio) (Max-SR, Max-STARR, Max Mean/MAD and Max Mean/CDaR). For mean-risk portfolio strategies, we set the target return to the average of the conditional means ($\mu^P = \frac{1}{d}\sum_{n=1}^{d} \widetilde{\mu}_n$). For each portfolio strategy, we first estimate the portfolio weights using corresponding optimization and based on these weights we estimate the realized returns by utilizing assets' weights with the returns' realizations. It is noteworthy that we re-estimate the whole procedure for each day in terms of out-of-sample period and perform the back-testing for each of the underlying technique to attain the portfolio returns. We set the out-of-sample period from March 2007 until April 2019. We evaluate the performance of copula-based portfolio against the benchmark portfolios including equally-weighted and portfolios obtained based on historical data. Four different risk measures are portfolio variance, MAD, CVaR and CDaR. To provide a comprehensive comparison of the portfolio strategies, we divide the out-of-sample analysis into (i) descriptive statistics, (ii) risk-adjusted and (iii) economic performance.

4.4 | Portfolios' out-of-sample descriptive statistics

Table 3 reports the descriptive statistics for out-of-sample portfolio returns. Panel A provides the results for the benchmark portfolios, while panels B–F present the results for copula-based portfolios.

Regarding the benchmark portfolios, we find that the average daily returns are negative. Specifically, the average return for the equally weighted portfolio is −0.039% with minimum and maximum return ranging from −10.94% to 12.27%, respectively. The average return for historically based portfolio ranges from −0.003% (mean-CVaR) to −0.041% (max mean/CDaR). Whereas the volatility of the historical-based portfolios ranges from 0.928% (mean–variance) to 1.429% (max mean/MAD), while the volatility of equally-weighted portfolio is highest (1.447%) among the benchmark portfolios. Interestingly, mean-CVaR and mean-CDaR portfolios are unable to outperform the mean–variance and mean-MAD portfolios in increasing the minimum returns. All of the optimal portfolios increase the maximum return at the cost of increased volatility. However, these portfolios are unable to increase the average return.

For the copula-based portfolios, all of the allocation methods are able to provide a positive average return, except for mean–variance. In terms of Student-*t* copula-based portfolios, the average return ranges from −0.005% (mean–variance) to 0.085% (max mean/MAD). Whereas the minimum and maximum average return is found in mean-MAD of −32.172% and 18.316%, respectively. Although the volatility of Student-*t* copula-based portfolios are higher than the benchmark portfolios, these portfolios significantly outperform the benchmark portfolios in terms of returns.

TABLE 3 Out-of-sample descriptive statistics

Portfolio strategies	Min	Max	Mean	*SD*	Skewness	Kurtosis
Panel A: Benchmark portfolios						
(i) EQW	−10.939	12.269	−0.039	1.447	−0.502	7.957
(ii) Historical-based portfolios						
Mean–Variance	−8.205	7.465	−0.006	0.928	−0.718	8.614
Mean-CVaR	−9.786	7.457	−0.003	0.944	−0.885	10.257
Mean-MAD	−7.67	7.692	−0.005	0.929	−0.659	9.027
Mean-CDaR	−10.041	6.869	−0.019	1.04	−0.634	8.812
Max-SR	−14.321	9.676	−0.04	1.399	−1.004	9.783
Max-STARR	−15.008	8.474	−0.039	1.372	−1.032	9.755
Max Mean/MAD	−14.323	10.78	−0.039	1.429	−0.993	10.989
Max Mean/CDaR	−16.978	13.647	−0.041	1.345	−1.148	19.648
Panel B: Student-*t* copula-based portfolios						
Mean–Variance	−16.787	17.402	−0.005	1.076	−0.408	44.353
Mean-CVaR	−17.43	13.398	0.025	0.981	−1.307	48.566
Mean-MAD	−32.172	18.316	0.016	1.46	−2.485	114.357
Mean-CDaR	−17.069	13.417	0.053	1.163	−1.207	26.375
Max-SR	−13.533	13.928	0.055	1.598	−0.362	9.935
Max-STARR	−15.515	8.652	0.077	1.565	−0.661	9.889
Max Mean/MAD	−15.894	10.842	0.085	1.602	−0.603	10.82
Max Mean/CDaR	−15.939	8.643	0.057	1.593	−0.994	11.555
Panel C: Clayton copula-based portfolios						
Mean–Variance	−16.009	7.962	−0.005	1.032	−1.689	24.113
Mean-CVaR	−18.356	7.603	0.022	0.974	−2.419	46.452
Mean-MAD	−23.442	47.817	0.044	1.772	8.96	246.278
Mean-CDaR	−16.214	34.59	0.064	1.352	6.196	174.222
Max-SR	−13.776	10.634	0.061	1.509	−0.385	8.451
Max-STARR	−11.579	9.844	0.091	1.631	−0.314	7.245
Max Mean/MAD	−15.384	9.344	0.079	1.5	−0.713	10.571
Max Mean/CDaR	−13.613	10.667	0.07	1.619	−0.738	10.987
Panel D: Joe copula-based portfolios						
Mean–Variance	−16.051	6.922	−0.009	1.02	−1.89	24.795
Mean-CVaR	−18.462	7.489	0.015	0.965	−2.526	48.152
Mean-MAD	−37.251	47.817	0.008	1.732	4.197	277.17
Mean-CDaR	−16.263	7.721	0.037	1.117	−1.555	21.175
Max-SR	−13.627	15.476	0.068	1.545	0.073	12.479
Max-STARR	−12.475	9.844	0.083	1.599	−0.376	7.341
Max Mean/MAD	−15.492	9.094	0.08	1.469	−0.69	11.207
Max Mean/CDaR	−13.592	11.037	0.069	1.564	−0.616	10.671
Panel E: Frank copula-based portfolios						
Mean–Variance	−15.087	7.188	−0.007	1.018	−1.667	20.692
Mean-CVaR	−16.634	7.7	0.023	0.943	−2.242	37.892
Mean-MAD	−32.172	43.086	0.028	1.557	4.396	262.624
Mean-CDaR	−18.986	7.26	0.046	1.14	−2.053	30.8

TABLE 3 (Continued)

Portfolio strategies	Min	Max	Mean	*SD*	Skewness	Kurtosis
Max-SR	−14.965	11.972	0.055	1.549	−0.464	10.516
Max-STARR	−24.131	10.282	0.06	1.532	−2.161	30.68
Max Mean/MAD	−26.892	10.825	0.084	1.674	−2.005	31.452
Max Mean/CDaR	−18.355	11.143	0.069	1.542	−1.269	15.327
Panel F: Mixed copula-based portfolios						
Mean–Variance	−16.466	16.239	0.001	1.065	−0.392	39.254
Mean-CVaR	−17.466	7.944	0.023	0.954	−2.235	42.184
Mean-MAD	−32.172	18.316	0.019	1.353	−4.056	140.13
Mean-CDaR	−18.167	15.362	0.067	1.172	−0.911	31.857
Max-SR	−11.564	12.386	0.07	1.54	−0.048	6.899
Max-STARR	−15.313	29.672	0.101	1.681	1.453	37.681
Max Mean/MAD	−14.524	29.672	0.12	1.742	1.314	33.381
Max Mean/CDaR	−14.674	29.672	0.094	1.677	1.473	38.357

Note: This table provides out-of-sample descriptive statistics for portfolio strategies' daily returns consisting of 28 energy market stocks. The results are obtained by applying rolling window estimation of the forecasting models simulating one-step ahead assets' returns. For each portfolio strategy, realized returns are calculated by performing the corresponding portfolio optimization and estimating and using the assets' weights with the returns' realizations. The estimation window includes 1000 days. The out-of-sample period is from March 2007 until April 2019. The benchmark portfolios include the equally-weighted and portfolios obtained based on historical data. All of the copula-based portfolios are obtained by applying truncated and thresholded Rvine models. The truncation and thresholding are performed by using mBICV criterion. In the mixed copula model, the copula families are also selected based on mBICV.

Similarly, regarding Clayton copula-based portfolios, the average portfolio returns range from −0.005% (mean–variance) to 0.085% (max mean/MAD). Analogous to Student-*t* copula-based portfolios, the minimum and maximum average portfolio return is reported by mean-MAD of −23.442% and 47.817%, respectively. In terms of volatility, mean-CVaR provides the lowest volatility of 0.974%, while mean-MAD provides the highest volatility of 1.772%. Similar results are reported for Joe copula- and Frank copula-based portfolios.

The maximum average returns among the copula-based portfolios are obtained from the mixed copula-based. The average returns range from 0.001% (mean–variance) to 0.12% (max mean/MAD). The higher returns reported by the mixed copula-based strategies are primarily at the cost of increased volatility. However, the increased volatility is not significantly higher from the other copula-based portfolios. Overall, these findings illustrate the potential of increased portfolio returns on investment due to lower dependence among the firms operating across the four underlying energy sectors by utilizing copula-based weights.

4.5 | Out-of-sample risk-adjusted performance

Table 4 presents the results of portfolios' risk-adjusted performance. Panel A provides an overview of risk-adjusted performance of benchmark portfolios, while panels B–F provide the results from copula-based portfolios.

In regard to benchmark portfolios, the historical-based portfolio performs relatively better than the equally weighted portfolio. In terms of risk-adjusted performance of historical-based portfolio, the lowest and highest MAD is reported for mean–variance (0.649%) and max mean/MAD (0.955%), respectively. The CVaR ranges from 3.93% (mean–variance) to 6.66% (max mean/MAD), while the lowest and highest CDaR is reported for mean-CVaR (0.38%) and max-STARR (0.68%), respectively. In terms of Sharpe ratio, the highest value is reported for mean-CVaR (−0.003) and the lowest value for max-SR (−0.029).

In terms of copula-based frameworks, the Student-*t* copula-based portfolio provides relatively higher values of MAD than the historical-based portfolios. Furthermore, the VaR and CVaR provide relatively similar outputs as those of historical-based copula. However, in terms of CDaR, the Student-*t* copula provides significantly lower values of deviation. In addition, the SR is positive for all the portfolios, except for mean–variance, in the Student-*t* copula-based portfolios, indicating an overall better risk adjusted performance in comparison with the historical-based portfolios. The Clayton-, Joe-, Frank and mixed copula-based portfolios provide similar performance over the historical-based copula.

Within the copula-based portfolios, the lowest MAD (0.631% and 0.639%) and CVaR (4.07% and 4.085%) are

TABLE 4 Out-of-sample risk-adjusted performance

Portfolio strategies	MAD	VaR	CVaR	CDaR	SR	Mean/MAD	Mean/VaR	STARR	Mean/CDaR
Panel A: Benchmark portfolios									
(i) EQW	0.993	4.298	6.296	0.602	−0.027	−0.04	−0.009	−0.006	−0.066
(ii) Historical-based portfolios									
Mean–Variance	0.649	2.703	3.938	0.397	−0.006	−0.009	−0.002	−0.001	−0.014
Mean-CVaR	0.659	2.742	4.097	0.383	−0.003	−0.004	−0.001	−0.001	−0.007
Mean-MAD	0.642	2.639	4.011	0.411	−0.005	−0.008	−0.002	−0.001	−0.013
Mean-CDaR	0.721	2.968	4.405	0.418	−0.018	−0.026	−0.006	−0.004	−0.045
Max-SR	0.947	4.367	6.345	0.669	−0.029	−0.042	−0.009	−0.006	−0.06
Max-STARR	0.944	4.151	6.007	0.686	−0.028	−0.042	−0.009	−0.007	−0.057
Max Mean/MAD	0.955	4.527	6.661	0.651	−0.027	−0.041	−0.009	−0.006	−0.06
Max Mean/CDaR	0.881	4.011	6.33	0.621	−0.03	−0.046	−0.01	−0.006	−0.066
Panel B: Student-t copula-based portfolios									
Mean–Variance	0.71	2.849	4.564	0.369	−0.005	−0.007	−0.002	−0.001	−0.014
Mean-CVaR	0.64	2.46	4.091	0.13	0.025	0.039	0.01	0.006	0.193
Mean-MAD	0.731	3.109	7.094	0.536	0.011	0.022	0.005	0.002	0.031
Mean-CDaR	0.761	3.35	5.366	0.13	0.046	0.069	0.016	0.01	0.406
Max-SR	1.064	4.871	6.746	0.392	0.034	0.052	0.011	0.008	0.14
Max-STARR	1.024	4.93	6.926	0.214	0.049	0.075	0.016	0.011	0.36
Max Mean/MAD	1.047	4.869	7.088	0.166	0.053	0.081	0.017	0.012	0.51
Max Mean/CDaR	1.04	4.766	7.292	0.177	0.036	0.054	0.012	0.008	0.32
Panel C: Clayton copula-based portfolios									
Mean–Variance	0.702	2.999	4.558	0.371	−0.005	−0.007	−0.002	−0.001	−0.014
Mean-CVaR	0.649	2.536	4.222	0.219	0.023	0.034	0.009	0.005	0.1
Mean-MAD	0.755	3.128	6.677	0.484	0.025	0.059	0.014	0.007	0.092
Mean-CDaR	0.766	3.25	5.135	0.199	0.047	0.083	0.02	0.012	0.319
Max-SR	1.022	4.456	6.139	0.322	0.04	0.06	0.014	0.01	0.19
Max-STARR	1.071	4.849	6.99	0.204	0.056	0.085	0.019	0.013	0.445
Max Mean/MAD	0.991	4.339	6.47	0.153	0.053	0.08	0.018	0.012	0.517
Max Mean/CDaR	1.043	4.717	7.538	0.301	0.043	0.067	0.015	0.009	0.231
Panel D: Joe copula-based portfolios									
Mean–Variance	0.696	2.849	4.579	0.397	−0.009	−0.013	−0.003	−0.002	−0.023
Mean-CVaR	0.645	2.607	4.139	0.397	0.016	0.023	0.006	0.004	0.037
Mean-MAD	0.746	3.298	7.598	0.606	0.005	0.011	0.003	0.001	0.014
Mean-CDaR	0.746	3.165	5	0.161	0.033	0.05	0.012	0.007	0.231
Max-SR	1.022	4.543	6.357	0.249	0.044	0.066	0.015	0.011	0.272
Max-STARR	1.061	4.656	6.749	0.182	0.052	0.078	0.018	0.012	0.456
Max Mean/MAD	0.975	4.135	6.265	0.163	0.054	0.082	0.019	0.013	0.492
Max Mean/CDaR	1.021	4.435	6.99	0.268	0.044	0.067	0.015	0.01	0.256
Panel E: Frank copula-based portfolios									
Mean–Variance	0.703	2.806	4.433	0.409	−0.007	−0.009	−0.002	−0.001	−0.016
Mean-CVaR	0.631	2.547	4.07	0.2	0.024	0.036	0.009	0.006	0.113
Mean-MAD	0.729	3.272	6.261	0.48	0.018	0.038	0.009	0.004	0.058
Mean-CDaR	0.753	3.164	5.325	0.166	0.04	0.061	0.014	0.009	0.276

TABLE 4 (Continued)

Portfolio strategies	MAD	VaR	CVaR	CDaR	SR	Mean/MAD	Mean/VaR	STARR	Mean/CDaR
Max-SR	1.037	4.565	6.488	0.393	0.036	0.053	0.012	0.008	0.14
Max-STARR	0.971	4.41	7.217	0.301	0.039	0.061	0.014	0.008	0.198
Max Mean/MAD	1.055	4.503	7.839	0.26	0.05	0.08	0.019	0.011	0.323
Max Mean/CDaR	0.998	4.59	7.149	0.202	0.045	0.069	0.015	0.01	0.34
Panel F: Mixed copula-based portfolios									
Mean–Variance	0.705	2.878	4.402	0.3	0.001	0.001	0	0	0.003
Mean-CVaR	0.639	2.499	4.085	0.186	0.024	0.035	0.009	0.006	0.122
Mean-MAD	0.704	2.661	6.424	0.504	0.014	0.027	0.007	0.003	0.037
Mean-CDaR	0.776	3.268	5.05	0.162	0.057	0.086	0.02	0.013	0.412
Max-SR	1.045	4.55	6.07	0.314	0.045	0.067	0.015	0.012	0.223
Max-STARR	1.048	4.661	6.722	0.296	0.06	0.096	0.022	0.015	0.341
Max Mean/MAD	1.088	5.046	7.098	0.225	0.069	0.111	0.024	0.017	0.535
Max Mean/CDaR	1.05	4.747	6.689	0.205	0.056	0.089	0.02	0.014	0.457

Note: This table provides out-of-sample risk-adjusted performance for portfolio strategies' daily returns consisting of 28 energy market stocks. The results are obtained by applying rolling window estimation of the forecasting models simulating one-step ahead assets' returns. For each portfolio strategy, realized returns are calculated by performing the corresponding portfolio optimization and estimating and using the assets' weights with the returns' realizations. The estimation window includes 1000 days. The out-of-sample period is from March 2007 until April 2019. The benchmark portfolios include the equally-weighted and portfolios obtained based on historical data. All of the copula-based portfolios are obtained by applying truncated and thresholded Rvine models. The truncation and thresholding is performed by using mBICV criterion. In the mixed copula model, the copula families are also selected based on mBICV. VaR, CVaR and CDaR are estimated empirically at 1% confidence level.

reported for mean-CVaR portfolios based on Frank and mixed copula models. This indicates the copula families which are sensitive to symmetric tail dependence (e.g., Frank) are more capable to reduce the portfolio downside risk for the energy stocks. On the other hand, the minimum CDaR (0.13%) is obtained based on the Student-*t* copula-based mean-CDaR portfolio. Regarding the out-of-sample mean/risk ratios, the mixed copula based optimal portfolios outperform corresponding portfolios obtained from other copula families. For instance, for max-SR portfolios, mixed copula model gives a Sharpe ratio of 0.045, which is the highest value among all the max-SR portfolios. However, the highest SR is reported for max mean/MAD portfolio (0.069%) for the mixed copula-based portfolio. Furthermore, this portfolio strategy also results in the higher STARR and mean/CDaR ratios.

The increased out-of-sample risk-adjusted performance is attributed to the addition of stocks from multiline utilities sector and renewables sector, compared with stocks from oil and gas sector and oil and gas related equipment and services sector. Specifically, assessment of dependence structure among the assets is crucial for estimating portfolio weights. Therefore, the consideration of heterogeneity of business cycles and idiosyncratic components of the firms operating across these four underlying sectors results in lower degrees of dependence among the assets, thereby providing the potential to attain portfolio diversification benefits. The lower dependence among the four sectors results in higher average return, which can be seen in Table 5. These findings add to the study of Antonakakis et al. (2018) and Ma et al. (2019) as they reported diversification potential between crude oil and firms operating within oil and gas sector. However, their study is limited to examination of spillover dynamics between crude oil and firms operating in oil and gas sector. In this regard, our paper significantly extends their study by examining the firm-level data from the perspective of four different sectors. These findings, in general, complements the results of Reboredo et al. (2017) as they reported lower dependence among oil and renewable indexes over the short-run. However, they utilize the aggregate data renewable index at sector level and thereby this study significantly extends the findings reported therein.

4.6 | Out-of-sample economic performance

To compare the portfolio strategies based on their economic performance, we use accumulation wealth. To compute the portfolios wealth, we consider daily rebalancing strategy with $100 initial investment. However,

TABLE 5 Out-of-sample economic performance

Portfolio strategies	Accumulation wealth	Accumulation wealth (TC = 1 bp)	Accumulation wealth (TC = 5 bp)	Ave. turnover
Panel A: Benchmark portfolios				
(i) EQW	20.604	20.604	20.604	0
(ii) Historical-based portfolios				
Mean–Variance	73.396	72.945	71.938	0.011
Mean-CVaR	79.642	79.008	77.276	0.017
Mean-MAD	73.659	73.008	71.13	0.02
Mean-CDaR	46.458	46.257	45.292	0.016
Max-SR	20.582	20.108	18.226	0.077
Max-STARR	21.362	20.767	18.39	0.096
Max Mean/MAD	20.992	20.444	18.311	0.087
Max Mean/CDaR	20.456	19.993	17.975	0.084
Panel B: Student-t copula-based portfolios				
Mean–Variance	70.595	59.441	29.785	0.547
Mean-CVaR	189.912	153.323	65.649	0.671
Mean-MAD	118.67	96.894	43.556	0.633
Mean-CDaR	422.794	284.466	57.413	1.266
Max-SR	380.534	245.402	43.342	1.372
Max-STARR	776.958	477.959	68.511	1.537
Max Mean/MAD	967.842	590.976	82.071	1.562
Max Mean/CDaR	396.732	240.59	32.209	1.591
Panel C: Clayton copula-based Portfolios				
Mean–Variance	71.608	61.201	32.553	0.499
Mean-CVaR	171.643	135.464	53.5	0.735
Mean-MAD	257.141	211.381	97.37	0.613
Mean-CDaR	568.262	381.841	78.905	1.248
Max-SR	479.362	314.468	58.091	1.336
Max-STARR	1149.823	695.349	93.084	1.591
Max Mean/MAD	845.057	521.29	75.577	1.528
Max Mean/CDaR	592.544	357.629	47.832	1.592
Panel D: Joe copula-based portfolios				
Mean–Variance	63.427	54.135	28.64	0.504
Mean-CVaR	137.445	108.221	42.223	0.745
Mean-MAD	81.618	67.131	30.866	0.615
Mean-CDaR	264.393	178.584	37.198	1.242
Max-SR	584.631	382.26	70.45	1.338
Max-STARR	912.015	553.594	74.925	1.583
Max Mean/MAD	887.519	551.63	82.143	1.507
Max Mean/CDaR	592.236	360.101	49.063	1.577
Panel E: Frank copula-based portfolios				
Mean–Variance	68.928	58.06	29.135	0.546
Mean-CVaR	176.655	144.357	64.233	0.641
Mean-MAD	166.065	134.064	57.269	0.673

TABLE 5 (Continued)

Portfolio strategies	Accumulation wealth	Accumulation wealth (TC = 1 bp)	Accumulation wealth (TC = 5 bp)	Ave. turnover
Mean-CDaR	345.031	231.934	47.143	1.261
Max-SR	387.963	253.515	46.358	1.344
Max-STARR	448.679	281.19	43.38	1.479
Max Mean/MAD	904.305	549.811	74.655	1.58
Max Mean/CDaR	595.311	363.155	49.159	1.582
Panel F: Mixed copula-based portfolios				
Mean–Variance	86.021	72.332	36.048	0.551
Mean-CVaR	176.422	142.404	60.711	0.675
Mean-MAD	133.328	108.906	48.767	0.636
Mean-CDaR	658.371	436.686	85.189	1.293
Max-SR	627.457	406.264	71.656	1.373
Max-STARR	1560.517	951.377	133.695	1.553
Max Mean/MAD	2780.648	1687.133	228.939	1.581
Max Mean/CDaR	1250.953	746.764	96.525	1.619

Note: This table provides out-of-sample economic performance for portfolio strategies' daily returns consisting of 28 energy market stocks. The results are obtained by applying rolling window estimation of the forecasting models simulating one-step ahead assets' returns. For each portfolio strategy, realized returns are calculated by performing the corresponding portfolio optimization and estimating and using the assets' weights with the returns' realizations. The estimation window includes 1000 days. The out-of-sample period is from March 2007 until April 2019. The benchmark portfolios include the equally-weighted and portfolios obtained based on historical data. All of the copula-based portfolios are obtained by applying truncated and thresholded Rvine models. The truncation and thresholding is performed by using mBICV criterion. In the mixed copula model, the copula families are also selected based on mBICV. The first column reports the portfolio wealth without considering the transaction costs. In the second and third column, portfolio wealth is calculated by using 1 and 5 basis points proportional transaction cost. The portfolio wealth is calculate based on daily re-balancing with $100 initial investment.

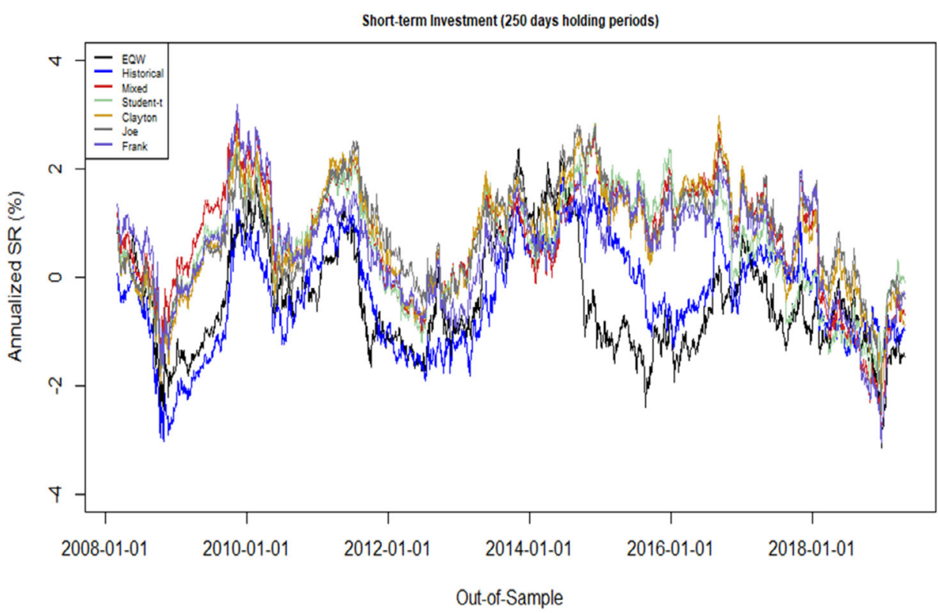

FIGURE 4 Multiperiod realized SR. this figure plots terminal values for annualized SR, with a holding period of 250 days, for max-SR portfolios [Colour figure can be viewed at wileyonlinelibrary.com]

one has to notice that the daily re-balancing strategy will increases the transaction costs. To account for the extra cost, we use proportional (and fixed) transaction costs at 1 and 5 basis points.

Table 5 provides the results for the economic performance of the portfolios. Regarding benchmarks, both the equally-weighted and historical-based portfolios are unable to increase the economic performance of the

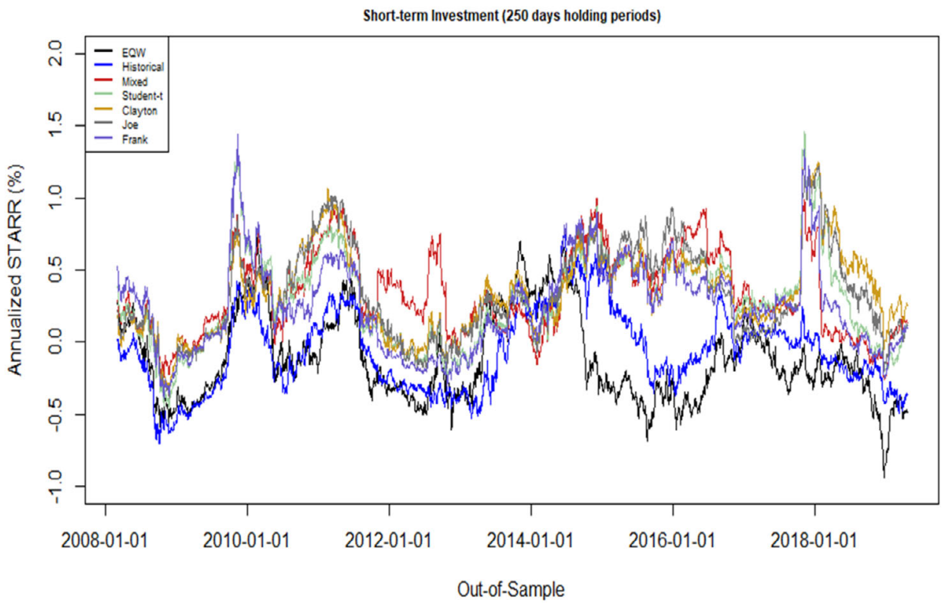

FIGURE 5 Multiperiod realized STARR. This figure plots terminal values for annualized STARR, with a holding period of 250 days, for max-STARR portfolios [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 6 Out-of-sample optimal weights

	Energy market sector			
Portfolio strategies	**Oil and gas**	**Oil and gas related equipment and servs**	**Multiline utilities**	**Renewable energy**
Panel A: Benchmark portfolios				
(i) EQW	25	25	25	25
(ii) Historical-based portfolios				
Mean–Variance	8.57	15.29	62.47	13.67
Mean-CVaR	7.69	15.22	64.41	12.68
Mean-MAD	13.19	14.42	60.47	11.92
Mean-CDaR	11.68	11.38	64.7	12.23
Max-SR	4.21	15.77	48.06	31.96
Max-STARR	3.84	14.42	49.78	31.95
Max Mean/MAD	4.38	15.64	48.43	31.55
Max Mean/CDaR	3.26	15.84	59.69	21.21
Panel B: Student-t copula-based portfolios				
Mean–Variance	18.12	21.89	49.23	10.76
Mean-CVaR	16.16	18.81	55.73	9.29
Mean-MAD	16.46	17.13	56.41	10
Mean-CDaR	15.48	18.59	51.63	14.3
Max-SR	16.83	23.15	35.94	24.07
Max-STARR	14.18	20.26	42.14	23.43
Max Mean/MAD	13.57	19.3	43.9	23.23
Max Mean/CDaR	13.81	19.94	41.76	24.49
Panel C: Clayton copula-based portfolios				
Mean–Variance	19.1	21.79	47.95	11.16
Mean-CVaR	15.77	18.66	55.67	9.9
Mean-MAD	17.14	17.35	54.37	11.14

TABLE 6 (Continued)

Portfolio strategies	Energy market sector: Oil and gas	Oil and gas related equipment and servs	Multiline utilities	Renewable energy
Mean-CDaR	16.02	19.2	50.16	14.62
Max-SR	17.31	23.56	35.45	23.68
Max-STARR	14.19	20.29	40.85	24.66
Max Mean/MAD	14.41	20.48	42.92	22.19
Max Mean/CDaR	14.04	20.52	40.38	25.06
Panel D: Joe copula-based portfolios				
Mean–Variance	19.19	21.51	47.22	12.08
Mean-CVaR	15.46	18.46	54.61	11.48
Mean-MAD	17.42	17.28	53.45	11.85
Mean-CDaR	15.94	19.32	49.2	15.55
Max-SR	17.51	23.25	35.08	24.15
Max-STARR	14.05	20.08	40.4	25.47
Max Mean/MAD	14.23	20.55	42.82	22.39
Max Mean/CDaR	13.95	20.59	39.78	25.67
Panel E: Frank copula-based portfolios				
Mean–Variance	18.8	21.51	49.14	10.55
Mean-CVaR	18.35	18.17	54.6	8.88
Mean-MAD	15.98	17.07	56.67	10.27
Mean-CDaR	16.14	18.88	50.68	14.3
Max-SR	17.25	23.39	35.92	23.43
Max-STARR	15.57	20.5	41.79	22.14
Max Mean/MAD	13.67	19.44	43.86	23.03
Max Mean/CDaR	14.47	20.38	41.05	24.11
Panel F: Mixed copula-based portfolios				
Mean–Variance	18.08	21.75	50.61	9.56
Mean-CVaR	16.36	18.8	57.15	7.69
Mean-MAD	16.78	17.03	57.54	8.65
Mean-CDaR	15.65	18.65	52.34	13.36
Max-SR	17	23.55	35.81	23.65
Max-STARR	13.73	20.99	42.67	22.6
Max Mean/MAD	13.3	19.96	43.85	22.89
Max Mean/CDaR	13.35	20.79	42.04	23.82

Note: This table provides relative contribution of each energy market sector in out-of-sample optimal weights for portfolio strategies' daily returns consisting of 28 energy market stocks. The numbers are in percentages and calculated as the ratio of total sum of the weights in each sector over the total sum of the portfolio weights.

investment. This can be seen from their high out-of-sample negative skewness and average returns. Furthermore, the highest economic performance appraisal is reported for mean-CVaR ($79.642).

In regard to copula-based forecasting models, the optimal portfolios outperform the mean-risk strategies. For mean-risk portfolios, in almost all cases, mean-CDaR strategy gives higher terminal value. In general, STARR, mean/MAD and mean/CDaR maximizations result in better economic performance comparing to SR maximization. Considering copula families, the mixed copula model results in higher portfolio accumulation wealth, even with five basis

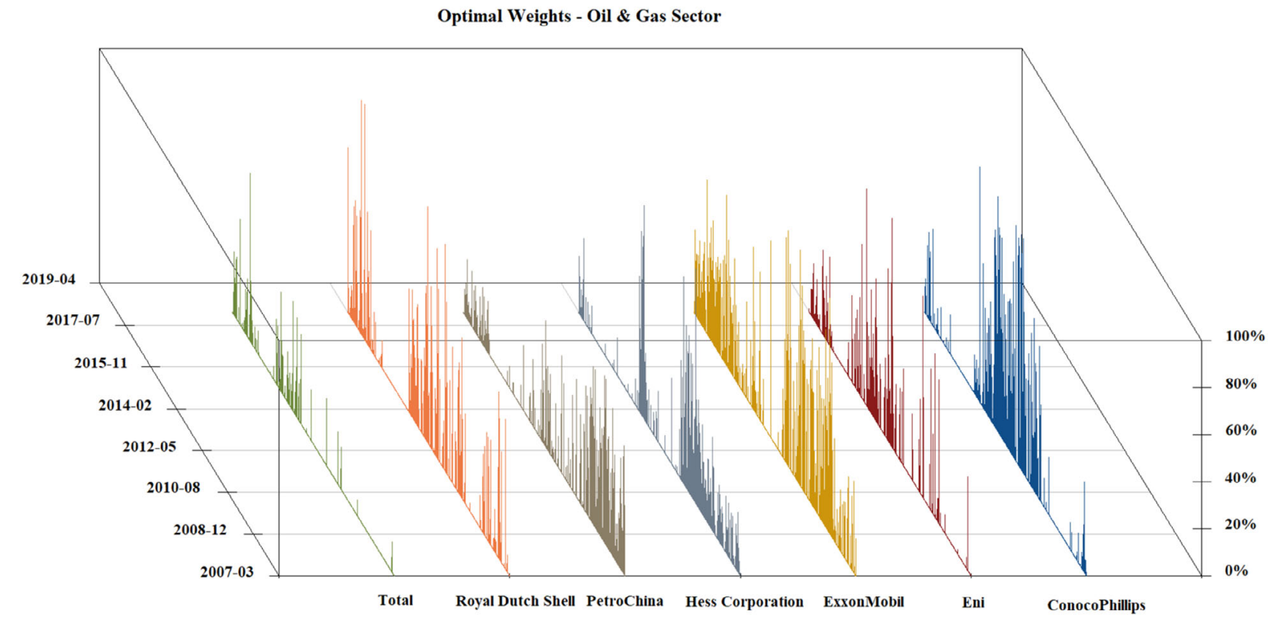

FIGURE 6 Max-STARR optimal weights (oil and gas) [Colour figure can be viewed at wileyonlinelibrary.com]

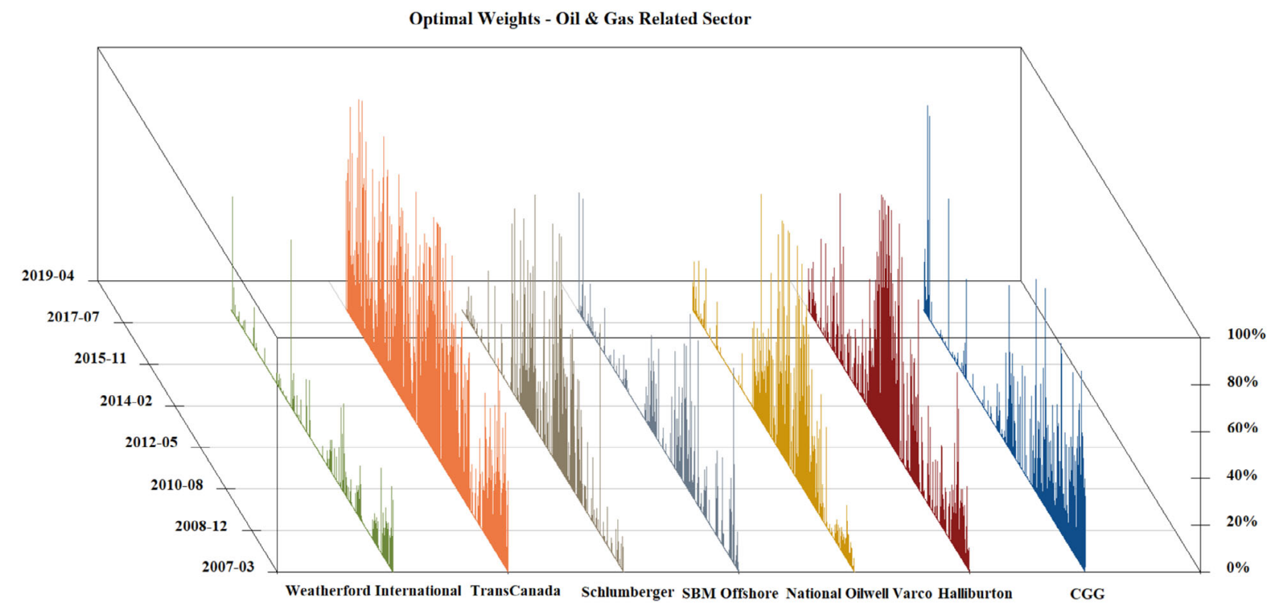

FIGURE 7 Max-STARR optimal weights (oil and gas related equipment and services) [Colour figure can be viewed at wileyonlinelibrary.com]

points transaction costs ($228.939). In terms of average turnover, which represents volume of assets' trades, optimal portfolios lead to higher turnover. This indicates that assets' weights have changed considerably during the out-of-sample period. Figures 4 and 5 show the multiperiod realized SR and STARR for the max-SR and max-STARR portfolio strategies using 250 days rolling window. It is noteworthy that the equally-weighted and the historical-based portfolios are significantly impact by the oil price shocks during 2015–2016. However, the copula-based max-SR, mean/MAD, mean/CDaR, and max-STARR portfolios seem to be not impacted by the oil price shock.

Table 6 provides the portfolio allocation weights across each of the portfolio. For instance, in an equally weighted portfolio, 25% of the portfolio weights should be invested across the four sectors. It is noteworthy that all the portfolio strategies are suggesting in allocating a significantly higher proportion of investment in the

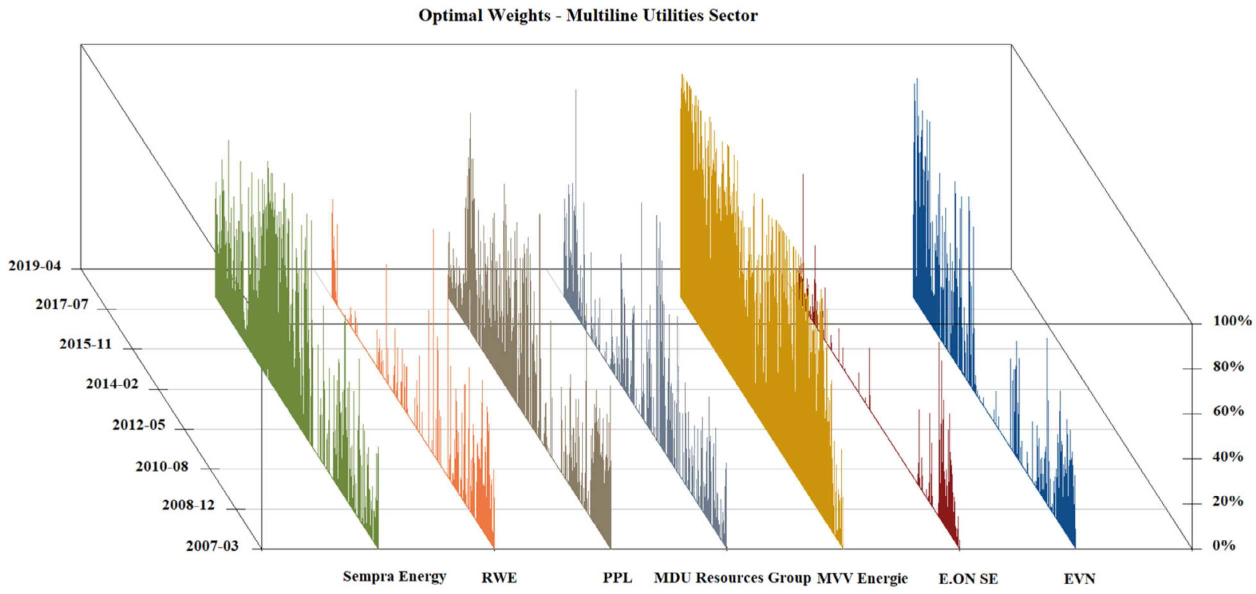

FIGURE 8 Max-STARR optimal weights (multiline utilities) [Colour figure can be viewed at wileyonlinelibrary.com]

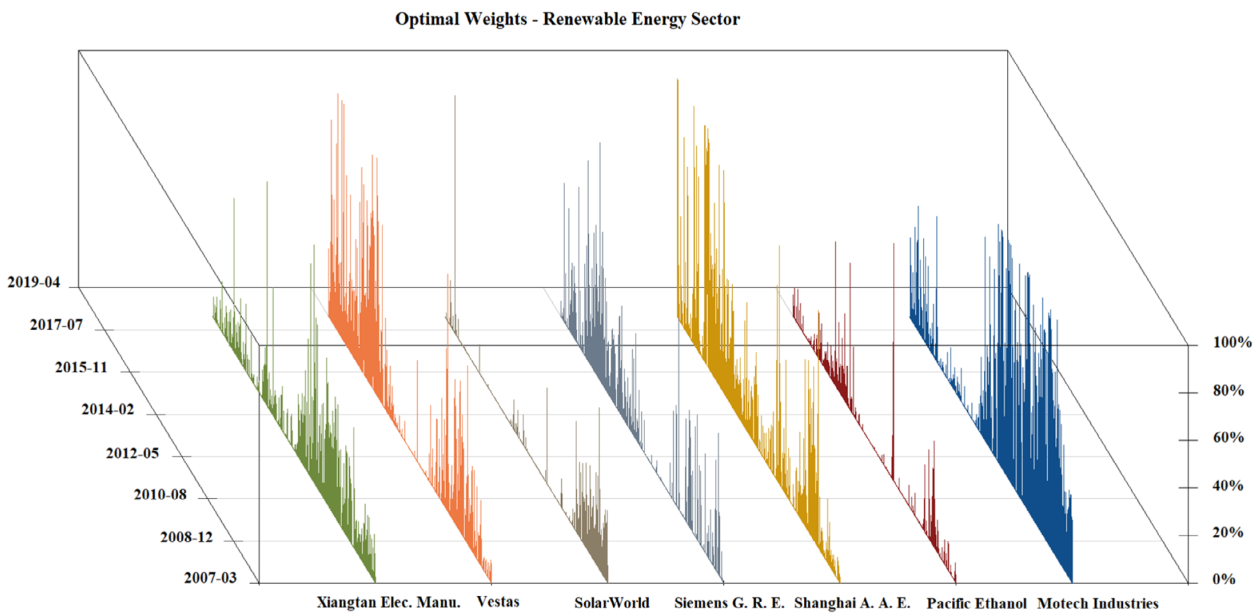

FIGURE 9 Max-STARR optimal weights (renewable energy) [Colour figure can be viewed at wileyonlinelibrary.com]

multiline utilities. This may be due to highly diversified operations and services of these firms and increased adaptability due to uncertainty, for instance drop in crude oil price. Figures 6–9 show the multiperiod weights for individual firms in each sector based on max-STARR portfolios.

Overall, these findings reflect the improvement of out-of-sample economic performance by utilizing stocks from the four sectors. Specifically, the consideration of heterogeneity of multiline utilities sector and renewables compared with the oil and gas sector and oil and gas related products and services sector results in lower connectedness structure, and thereby generating better out-of-sample economic performance. In terms of utilized frameworks, the copula-based portfolio strategies may be developed due to their ability to undertake both symmetric and asymmetric tail dependence in order to attain potential portfolio diversification and risk management benefits by investing in firms operating across the four underlying sectors.

5 | CONCLUSION

In this article, we investigate the relationship among four energy sectors, including the oil and gas sector, oil and gas related equipment and services sector, multiline utilities sector, and renewables sector, in terms of their firm-level dependency structure. We further evaluate the diversification potential gained from multivariate portfolio strategies consisting of several firms operating in the energy sectors. In doing so, this study includes modelling dependency structure between the targeted firms, estimating return's conditional distribution, maximizing investor's utility function for several strategies, and performing portfolio back-testing.

Our results of dependency structure estimation, using truncated and thresholded Rvine model, show that in long-term, there exists both symmetric and asymmetric tail dependence among the energy market firms. In general, oil and gas and oil and gas related equipment and services sectors have the highest level of dependency. However, firms within the multiline utilities sector and renewable energy sector show lowest dependency with those from other sectors.

The result of portfolio back-testing indicate advantages obtained by constructing portfolio strategies using firm-level data from the energy markets. We found the potential of higher portfolio returns on investment in the four energy sectors by utilizing copula-based forecasting models. This indicates the importance of the dependency level among the four energy market sectors when constructing portfolio strategies. Furthermore, the results of out-of-sample risk-adjusted performance show improvements from mixed copula-based portfolios. In accordance with the results of dependency structure estimation, this unveils the existence of both symmetric and asymmetric tail dependence among energy sectors.

The outcomes of this article are of promising interest to policymakers, large oil and gas producers, portfolio managers and investors. The increasing investment in renewables reflects a manifestation of growing awareness concerning climate change. Global oil and gas producers and influential financial players are undertaking the issue of climate change by increasing or diverting their investments from traditional fossil fuel markets to the renewables. Although the cost of long-term energy transition is estimated to be \$1.7 trillion annually, the economic cost-saving from this investment is \$6 trillion (IRENA, 2018). In this regard, the time-varying dependence among the four sectors requires policymakers to develop and formulate policies that further decouples the impact of interconnectedness between the four sectors. Policymakers and regulators may devise a 'road map' based on the symmetric and asymmetric tail-dependence that facilitate the firms operating in oil and gas sector in easier transition towards the more sustainable renewable energy sector. Therefore, understanding the disaggregated-level stock market relationship is fundamental for policymakers in distinguishing between systemic and idiosyncratic information prevailing the firms operating across these four sectors. In regard to portfolio managers and international investors, assessing the connectedness structure among the underlying assets is crucial to formulate portfolio optimization and risk management decisions. Furthermore, it is essential to model tail-dependence and joint extreme movement among the underlying assets for devising portfolio allocation, risk management, and asset pricing decisions. Our findings also have important implications for impact investing, where the investor seeks to create social, commercial and environmental value. First, the current study provides the impact investors with an understanding of the performance of firms in renewable energy, in terms of portfolio diversification, relative to those in other energy sector markets. Second, as we find low levels of tail dependency, the renewable energy sector can provide not only environmental added-values but also hedge and insurance strategies. Overall, this article has significant implications for portfolio managers and investors aiming to manage the portfolio uncertainty, and also for policymakers targeting at lowering the dependence on fossil fuels and promoting the development of renewables.

For future research, we suggest investigating portfolio strategies based on each energy sector and evaluate possible gains for investors, also in terms of hedge and safe haven properties of these types of portfolios. In the current study, the main intuition for including all the energy sectors is to evaluate the renewable energy sector relative to others, with a view on both dependence structure and proportion of investment based on different portfolio strategies. Furthermore, the portfolio strategies in the current study are based on the assumption of rational investors. However, it is widely argued that investors can show irrational behaviour and are exposed to various biases. As in the current study, the portfolio strategies are purely based on utility function maximization, it would be difficult to extend our findings to irrational investments. This requires including irrational behaviours, for example, asymmetric risk-taking, probability weighting, and loss-aversion, and asymmetric risk-taking when defining the portfolio problem. Therefore, as another suggestion for future research, these different behaviours could be investigated concerning investment in energy market sectors.

ENDNOTES

[1] Note that $\widetilde{\boldsymbol{r}}_t$ is an $M \times d$ matrix of simulated returns.

[2] Note the notation t is still for the out-of-sample iteration. Due to our simulation approach, we use m as the time path in the original formula.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Datastream (published by Thomson Reuters). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Thomson Reuters.

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APPENDIX A

A d-dimensional portfolio consists of asset returns $\widetilde{r}_t = \left(\widetilde{r}_t^1, \widetilde{r}_t^2, \ldots, \widetilde{r}_t^M\right), \widetilde{r}_t^m = \left(\widetilde{r}_{1t}^m, \widetilde{r}_{2t}^m, \ldots, \widetilde{r}_{dt}^m\right)$ and asset weights $w_t = (w_{1t}, w_{2t}, \ldots, w_{dt})$.[1] Considering the mean vector $\widetilde{\mu}_t = (\widetilde{\mu}_1, \widetilde{\mu}_2, \ldots, \widetilde{\mu}_d)$ and $d \times d$ positive-definite covariance matrix $\widetilde{\mathrm{H}}_t = cov(\widetilde{r}_t)$, the first (expected return) and second (variance) moments of the portfolio returns are $w_t^\top \widetilde{\mu}_t$ and $w_t^\top \widetilde{\mathrm{H}}_t w_t$. Note that the mean vector $\widetilde{\mu}_t$ includes the conditional mean vector from the AR-GARCH model and the covariance matrix $\widetilde{\mathrm{H}}_t$ is calculated from the simulated returns $\widetilde{r}_t$. By doing this, one can preserve the dependency structure estimated in the copula modelling and the general conditional (joint) distribution in the optimization system. Therefore, not only the classical risk measure (variance) but also the tail risk measures can be used in the asset allocation.

Markowitz (1952) suggested the portfolio variance as a valid measure of uncertainty in a scenario-based allocation. The Markowitz's mean–variance portfolio allows the investor to reduce the risk given a certain (or minimum) level of reward. This minimization of portfolio variance in its quadratic form can be expressed as:

$$\begin{array}{ll} \underset{w_t}{\text{minimize}} & w_t^{\mathrm{T}}\widetilde{\mathrm{H}}_t w_t \\ \text{Subject to}: & w_t^{\mathrm{T}}\widetilde{\mu}_t \geq \mu^P \\ & w_t^{\mathrm{T}} 1 = 1 \\ & \forall n \in \{1,2,...,d\} : w_{nt} \geq 0 \end{array} , \tag{A1}$$

where, μ^P is the minimum portfolio reward (expected return) requested by the investor. The second and third linear constraints impose full investment and long only position.

In an extension of the Markowitz's mean–variance spectrum, Konno and Yamazaki (1991) suggested the absolute deviation as an alternative to variance. The minimization problem is originally nonlinear; however, Konno and Yamazaki (1991) derived the linear form of the mean-MAD optimization by introducing auxiliary variables $\mathfrak{I} = (\mathfrak{I}^1, \mathfrak{I}^2, ..., \mathfrak{I}^M)$ representing the absolute deviation of portfolio returns from the expected portfolio mean. Given a minimum level of reward (μ^P), the linearized form of the mean-absolute deviation is:

$$\begin{array}{ll} \underset{w_t, \mathfrak{I}}{\text{minimize}} & \overline{\mathfrak{I}} \\ \text{Subject to}: & \forall m \in \{1,2,...,M\} : w_t^{\mathrm{T}} a^m \leq \mathfrak{I}^m \\ & \forall m \in \{1,2,...,M\} : w_t^{\mathrm{T}} a^m \geq -\mathfrak{I}^m \\ & w_t^{\mathrm{T}}\widetilde{\mu}_t \geq \mu^P \\ & w_t^{\mathrm{T}} 1 = 1 \\ & \forall n \in \{1,2,...,d\} : w_{nt} \geq 0 \end{array} , \tag{A2}$$

where, $\overline{\mathfrak{I}} = \frac{1}{M}\sum_{m=1}^{M} \mathfrak{I}^m$, and $a^m = (a_1^m, a_2^m, ..., a_d^m)$ denotes a vector of asset's returns deviation from their mean ($a_n^m = \widetilde{r}_{nt}^m - \widetilde{\mu}_{nt}$).

Conditional value-at-risk (CVaR) is another risk measure that has superiority to variance or even the well-known VaR (see e.g., Embrechts et al. (1999); Rockafellar and Uryasev (2002). CVaR is defined as the probability of losses exceeding the VaR. Let $\Gamma(\widetilde{r}_t, w_t)$ and $\mathcal{P}(\widetilde{r}_t, w_t)$ be the loss and probability functions for the portfolio returns. Denoting υ_α as the α-level VaR, the α-level CVaR in its integral form is:

$$\mathrm{CVaR}_\alpha = \upsilon_\alpha + \frac{1}{1-\alpha}\int_{\Gamma(\widetilde{r}_t, w_t)}^{\upsilon_\alpha} \Gamma(\widetilde{r}_t, w_t)\mathcal{P}(\widetilde{r}_t, w_t) d\widetilde{r}_t, \tag{A3}$$

where, $\alpha \in [0,1]$. Rockafellar and Uryasev (2000) suggested a linearized form for minimization of CVaR, in which auxiliary variables $\mathfrak{H} = (\mathfrak{H}^1, \mathfrak{H}^2, ..., \mathfrak{H}^M)$, representing the deviation below the VaR, are added to the objective function. The linearized mean-CVaR portfolio optimization can be posed as:

$$\begin{array}{ll} \underset{w_t, \mathfrak{H}, \upsilon_\alpha}{\text{minimize}} & \upsilon_\alpha + 1/(1-\alpha)M \sum_{m=1}^{m} \mathfrak{H}^m \\ \text{Subject to}: & \forall m \in \{1,2,...,M\} : w_t^{\mathrm{T}}\widetilde{r}_t^{\,m} + \upsilon_\alpha \geq -\mathfrak{H}^m \\ & \forall m \in \{1,2,...,M\} : \mathfrak{H}^m \geq 0 \\ & w_t^{\mathrm{T}}\widetilde{\mu}_t \geq \mu^P \\ & w_t^{\mathrm{T}} 1 = 1 \\ & \forall n \in \{1,2,...,d\} : w_{nt} \geq 0 \end{array} . \tag{A4}$$

Chekhlov et al. (2005) suggested another risk measure incorporating the portfolio drawdown, which is defined as the drop in the uncompounded value of the portfolio comparing to the maximum portfolio value obtained at a previous time point over a sample period. Let $\Phi(\widetilde{r}_t, w_t, m) = \max_{0 \leq \kappa \leq m}\left\{\widetilde{\vartheta}_\kappa(w_t)\right\} - \widetilde{\vartheta}_m(w_t)$ and $\mathcal{P}(\widetilde{r}_t, w_t, m)$ be the function and probability distribution for the portfolio drawdowns.[2] Denoting η_α as the α-level threshold, the α-level CDaR in its integral form is:

$$\mathrm{CDaR}_\alpha = \eta_\alpha + \frac{1}{1-\alpha}\int_{\Phi(\widetilde{r}_t, w_t, m)}^{\eta_\alpha} \Phi(\widetilde{r}_t, w_t, m)\mathcal{P}(\widetilde{r}_t, w_t, m) dm, \tag{A5}$$

where, $\widetilde{\vartheta}_m(w_t) = \sum_{n=1}^{d}(1 + \sum_{s=1}^{m}\widetilde{r}_{nt}^{\,s})w_{nt}$ is the uncompounded portfolio value at time m and $\alpha \in [0,1]$. Following Chekhlov et al. (2004); Chekhlov et al. (2005), the linearization of mean-CDaR portfolio can be obtained by introducing auxiliary variables $\mathfrak{Z} = (\mathfrak{Z}^1, \mathfrak{Z}^2, ..., \mathfrak{Z}^M)$ and $\mathfrak{U} = (\mathfrak{U}^1, \mathfrak{U}^2, ..., \mathfrak{U}^M)$ denoting conditional drawdowns and cumulative returns, respectively. The linearized mean-CDaR portfolio optimization may be posed as:

$$\begin{array}{ll} \underset{w_t, \mathfrak{Z}, \mathfrak{U}, \eta_\alpha}{\text{minimize}} & \eta_\alpha + 1/(1-\alpha)M \sum_{m=1}^{M} \mathfrak{Z}^m \\ \text{Subject to}: & \forall m \in \{1,2,...,M\} : \mathfrak{Z}^m \geq \mathfrak{U}^m - \eta_\alpha \\ & \forall m \in \{1,2,...,M\} : w_t^{\mathrm{T}}\widetilde{r}_t^{\,m} + \mathfrak{U}^m \geq \mathfrak{U}^{m-1} \\ & \forall m \in \{1,2,...,M\} : \mathfrak{Z}^m \geq 0, \mathfrak{U}^m \geq 0 \\ & \mathfrak{U}^0 = 0 \\ & w_t^{\mathrm{T}}\widetilde{\mu}_t \geq \mu^P \\ & w_t^{\mathrm{T}} 1 = 1 \\ & \forall n \in \{1,2,...,d\} : w_{nt} \geq 0 \end{array} . \tag{A6}$$

Due to the fact that all of the risk measures considered above are convex and positive homogeneous, fractional programming can be applied to obtain maximum reward–risk optimization. Let $\Theta^{\mathrm{risk}}(\widehat{w}_t,\widetilde{r}_t)$, $\Theta^{\mathrm{reward}}(\widehat{w}_t,\widetilde{r}_t)$ be the general risk and reward functions, the reward–risk maximization can be formulated using the fractional programming as (Ghalanos, 2016):

$$\begin{array}{ll} \underset{\widehat{w}_t,\mathfrak{F}}{\text{minimize}} & \theta^{\mathrm{risk}}(\widehat{w}_t,\widetilde{r}_t) \\ & \theta^{\mathrm{reward}}(\widehat{w}_t,\widetilde{r}_t) \geq 1 \\ & \widehat{w}_t^{\mathrm{T}} 1 = \mathfrak{F} \\ & \mathfrak{F}\mathrm{L} \leq \mathrm{A}\widehat{w}_t \leq \mathfrak{F}\mathrm{U} \\ \text{Subject to:} & \mathfrak{F} > 0 \end{array}, \tag{A7}$$

where, $\widehat{w}_t = \mathfrak{F} w_t$ is a vector of unconstrained weights, $\mathfrak{F}$ denotes an auxiliary scaling variable, with A, L, U consist of linear constraints, lower and upper boundaries, respectively.