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Are oil and gas stocks from the Australian market riskier than coal and uranium stocks? Dependence risk analysis and portfolio optimization

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ABSTRACT

This article models the dependence risk and resource allocation characteristics of two 20-stock coal–uranium and oil–gas sector portfolios from the Australian market in the context of the global financial crisis of 2008–2009. The modeling framework implemented consists of pair vine copulas and, linear and nonlinear portfolio optimization methods with respect to five risk measures. The paper's objectives are to find out if the oil and gas stocks are riskier than the coal and uranium stocks, to identify the optimization method and risk measure that produce the best risk-return trade-off, to recognize the stocks in which the optimal weight allocations converge on average, and to acknowledge the vine copula model that best accounts for the overall dependence of the energy portfolios. The research findings indicate that the oil stocks have higher dependence risk than the coal, uranium and gas stocks in financial crisis periods. The higher risk of the oil stocks is confirmed by the larger concentration of symmetric and asymmetric dependence they have in the negative tail. The canonical vine (c-vine) copula model is observed to better capture the overall dependence of the energy portfolios. The combination of a pair c-vine copula and nonlinear portfolio optimization produces the highest return relative to risk. The optimal weight allocations converge on average in some stocks.

1. Introduction

According to the Australian Bureau of Resources and Energy Economics in 2014 Australia was the ninth largest producer of energy worldwide. In the period 2011–2012 the country exported roughly 80% of the energy it produced, with coal, uranium and gas accounting for 60, 20 and 13% of the exports, respectively. As of December 2012 the percentages of mining (coal and uranium are included in this category) and energy (e.g. oil, gas and renewables) stocks listed on the Australian Securities Exchange (ASX) were approximately 39 and 9, an indication of the large size of the energy sector and the relationship of dependence the sector has with the economy (Arreola and Powell, 2013). Since the global financial crisis of 2008–2009 there has been a renewed interest in quantifying the dynamics of dependence and resource allocation characteristics of energy markets by applying new techniques for dependence estimation and portfolio optimization.

This article models the dependence risk and resource allocation characteristics of two 20-stock coal-uranium and oil–gas sector portfolios from the Australian market in the context of the global financial crisis of 2008–2009. Canonical vine copulas (*c-vines*) and drawable vine copulas (*d-vines*) are fitted to estimate the dependence structure of the energy portfolios and understand their dependence risk characteristics. In addition to that, linear and nonlinear optimization methods with respect to five risk measures are implemented to investigate the resource allocation features of the portfolios. The paper's objectives are to find out if the oil and gas stocks are riskier than the coal and uranium stocks, to identify the optimization method and risk measure that produce the best risk-return trade-off, to recognize the stocks in which the optimal weight allocations converge on average, and to acknowledge the vine copula model that best accounts for the overall dependence of the portfolios.

The pair vine copula models considered for the analysis of the portfolio's dependence risk are suitable because they overcome the restrictive and deterministic features of the bivariate copulas and traditional measures of correlation (Brechmann and Czado, 2013). The multiple optimization methods and risk measures selected are desirable because they produce an array of investment scenarios that sets the ground for the search of the stocks in which the optimal weight allocations converge on average. The motivation for the selection of the coal, uranium, oil and gas stocks to implement the pair vine copula and portfolio optimization modeling framework proposed is that energy investors are increasingly considering them to diversify their portfolios (Gelder et al., 2011).

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The article first contributes to the related literature by unveiling in a thorough and detailed manner the dependence risk features of the portfolios in specific market conditions. This specific type of information could effectively be used to improve the hedging, risk management and rebalancing of energy portfolios. Another contribution stems from the implementation of various optimization methods and risk measures that caters for the risk and return preferences of energy investors, allows to compare the portfolio optimization model specifications in terms of risk-return trade-off, and sets the ground for the search of the stocks in which the optimal weight allocation converge on average (Krokhmal and Chen, 2006; Ortobelli et al., 2005). The paper's third contribution arises from the fitting of a combined modeling approach consisting of pair vine copulas and nonlinear portfolio optimization. This approach, as compared to those of the linear type, is expected to better grasp the risk and return features of the portfolios.

The vine copula modeling considered in this article is broadly linked to Berg and Aas' (2009) c-vine and d-vine estimations of dependence between two energy and two IT stock securities; and Mendes et al.'s (2010) d-vine modeling of dependence and portfolio optimization of six indices from Brazil. The modeling of negative tail dependence of European indices by Nikoloulopoulos et al. (2012) connects to this article's research in the consideration of a financial crisis event and financial period scenarios revolving around that event. In line with the research conducted by Wen et al. (2012), Aloui et al. (2013) and Tong et al. (2013), this article also investigates the dependence risk of energy markets. As compared to the above-mentioned studies, the vine copula modeling of dependence pursued in the present article has the advantage of identifying both, the dependence risk characteristics of the energy portfolios and the market conditions under which a portfolio has higher dependence risk than the other.

The studies by Chang et al. (2011), Delarue et al. (2011), Arreola et al. (2013) and Arreola and Powell (2013) relate to this article in the optimization of energy portfolios. Arreola and Powell (2013) estimate the dependence and optimize, with respect to five risk measures, two mining and two energy portfolios from the Australian market. Arreola et al. (2013) investigate the dependence matrix and optimize a 20-stock mix-metal leptokurtic portfolio also from the Australian market. Both studies have in common the use of a Gaussian pair vine copula to account for the dependence structure of the portfolios, which is fed into different portfolio optimization techniques. While some of the energy stocks modeled in Arreola and Powell (2013) are also considered in the present article, the modeling framework and data sets considered by both studies have significant differences.

The results indicate that the oil stocks have higher dependence risk than the coal, uranium and gas stocks in financial crisis periods. The higher risk of the oil stocks is confirmed by the larger concentration of symmetric and asymmetric dependence they have in the negative tail. The c-vine model is observed to better account for the overall dependence of the energy portfolios. The combination of a pair c-vine copula and the nonlinear mean-variance quadratic portfolio optimization produces the highest return relative to risk. The optimal weight allocations converge on average in the Cue Energy (CUEX), Woodside Petroleum (WPLX), Origin Energy (ORGX) and APA Group (APAX) stocks for the oil–gas portfolio. For the coal–uranium portfolio the portfolio optimization model specifications converge on average in the Leopard Resources (LRRX), Galilee Energy (GLLX), Energy Resources of Australia (EMAX), Blackwood (BWDX) and Paladin Energy (PDNX) stocks. While these stocks could be good candidates for investment, the overall findings may be relevant to energy portfolio investors, risk managers and dynamic hedging practitioners who follow the trends of the oil, gas, coal and uranium stocks.

The remainder of this article is organized as follows: Section 2 introduces the pair vine copula, portfolio optimization and risk measure models; Section 3 presents the data sets; Section 4 discusses the results and; Section 5 concludes the study.

2. Methodology

2.1. Pair vines copulas

Pair vine copulas are flexible graphical tree models that make possible the design and measurement of high dimensional multivariate distributions. Their flexibility, which is built in the theory of graphs, enables a localized and specific-specialized modeling of distributional features such as kurtosis, skewness, symmetric and asymmetric dependence through the use of bivariate copulas as the building blocks (Brechmann and Schepsmeier, 2011; Czado, 2010; Czado et al., 2012). The pair vine copulas' building blocks are central to the analysis of dependence because of their ability to grasp the dependence from the joint distribution while maintaining the original distribution of the marginals (Patton, 2012). Besides, they overcome the restrictive and deterministic features of traditional measures of correlation (e.g. the Pearson) and, a large set of bivariate copula families exist that can model joint distributions of varied characteristics (Low et al., 2013; Min and Czado, 2010). The theorem of Sklar (1959) laid the statistical framework that led to the development of the bivariate copula and pair vine copula models. Bedford and Cooke (2001, 2002) were the first to employ regular vine trees (*r-vines*) to organize and specify multivariate statistical models intended to capture the distribution of high dimensional data sets. For details about the connection between the theorem of Sklar and the pair vine copula models see Brechmann and Schepsmeier (2011).

2.1.1. Canonical and drawable vines

A *vine* V is a graphical structure of n elements so that in $V = (T_1,\ldots,T_{n-1})$ every T_i is a connected tree with nodes $N_i = E_{i-1}$ and edge set E_i (Kurowicka and Cooke, 2006). An *r-vine* is considered to be a *c-vine* if its trees consist of nodes and edges and, each tree T_i has a unique node of degree $n - i$. The node with the maximal degree in T_1 of the c-vine is the root node. An *r-vine* is considered to be a *d-vine* if each node in T_i has a degree of at most 2. Both, c-vines and d-vines are subject to the proximity condition which states that for $i = 2,\ldots,n-1$, if $\{a,b\} \in E_i$, then $\# a\Delta b = 2$. That is, if a and b are nodes of a tree T_i connected by an edge, where $a = \{a_1,a_2\}$ and $b = \{b_1,b_2\}$, then exactly one of the a_i equals one of the b_i. The symbol Δ denotes a union without the intersection. The c-vine and d-vine copula models are subsets of the set of r-vines.

The c-vines have a starlike shape and, for every tree T_i, $i \in \{1,\ldots,n-1\}$, a root node-variable is selected based on the criterion of having the highest correlation values with the rest of the variables. In addition to that, a root node-variable is selected for the entire vine structure. This root node is located in the first tree of the vine and is the most influential. The c-vine copula models are indicated to best suit data sets where there is a variable that has exceptionally high correlation values with the rest of the variables (Czado et al., 2013). The d-vines come in the form of line trees, and every node of any T_i cannot be linked to more than two edges. This type of vine copula model is indicated to better fit datasets where there is not a single variable that exerts exceptional influence on the others through high correlation values. Instead, all the variables in the first tree of the vine play a defining role in subsequent trees and the entire vine structure (Min and Czado, 2010).

The following models have been proposed by Aas et al. (2009) to separate multivariate densities and infer pair c-vine and pair d-vine copula structures:

$$f(\boldsymbol{x}) = \prod_{k=1}^{n} f_k(x_k) \cdot \prod_{i=1}^{n-1}\prod_{j=1}^{n-i} c_{i,i+j|1:(i-1)}\left(\mathrm{F}(x_i|x_1,\ldots x_{i-1}),\mathrm{F}\left(x_{i+j}\middle|x_1,\ldots,x_{i-1}\right)\middle|\boldsymbol{\theta}_{i,i+j|\,1:(i-1)}\right) \tag{1}$$