Energy Economics 66 (2017) 493–507

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Hedging downside risk of oil refineries: A vine copula approach

Kunlapath Sukcharoen *, David J. Leatham

Department of Agricultural Economics, Texas A&M University, United States

ARTICLE INFO

Article history:
Received 25 June 2016
Received in revised form 19 July 2017
Accepted 24 July 2017
Available online 5 August 2017

JEL codes:
C53
C58
G11
G17
G32
Q40

Keywords:
Downside risk
Energy hedging
Futures hedging
Multiproduct hedging
Vine copula

ABSTRACT

The financial health of an oil refinery greatly depends on its refining margin or the difference between the prices of its refined products (typically, gasoline and heating oil) and the cost of crude oil. The refinery may hedge against the downside risk of unfavorable price movements using crude oil, gasoline, and heating oil futures. This paper examines the use of a vine copula approach to estimate multiproduct hedge ratios that minimize the downside risk of the refinery. The advantage of the vine copula approach is that it allows us to capture important characteristics of petroleum price changes, including skewness and fat-tailedness in the marginal distributions of individual price change series as well as heterogeneous (tail) dependence patterns between different pairs of price changes. The out-of-sample hedging effectiveness of two popular classes of vine copula models – canonical (C-) and drawable (D-) vine copula models – are evaluated and compared with that of the widely used nonparametric method and three standard multivariate copula models. The empirical results reveal that the D-vine copula model is a good and safe choice in managing the downside risk of the refinery.

1. Introduction

A typical oil refinery purchases crude oil and sells refined products (e.g., gasoline and heating oil). Its refining or profit margin is then related to the spread between the prices of refined products and the price of crude oil. Thus, the refinery faces downside risk in both crude oil and refined product markets. As can be seen from Fig. 1, since late 2005, a large decline in the refining margin (due to the simultaneous adverse movements in the petroleum prices) has appeared to be quite common. The risk of losses because of unfavorable petroleum price movements clearly signifies the importance of hedging the joint downside risk of input and output prices. Accordingly, the goal of this paper is to develop a multiproduct futures hedging model that minimizes the downside risk of the refinery.[1]

Solving for the minimum-downside risk hedge ratios requires the estimation of the entire joint distribution of spot and futures price movements. For single-product hedging, the standard practice is to rely on a nonparametric method – in particular, the empirical distribution or historical simulation method (Lien and Tse, 2000; Demirer and Lien, 2003; Harris and Shen, 2006). This approach is very flexible and could be easily extended to the case of multiproduct hedging. However, it often produces inaccurate estimates of extreme quantiles due to its heavy dependence on historical data (McNeil and Frey, 2000; Pritsker, 2006; Cao et al., 2010). Recently, Barbi and Romagnoli (2014) propose a standard bivariate Archimedean copula model for estimating downside-risk hedge ratios in a single-product setting. They show that their proposed method produces greater downside risk reductions than the nonparametric approach. The superior performance is likely due to the model's ability to capture important characteristics of asset returns, including skewness and fat-tailedness in the distributions of individual asset returns as well as their nonlinear and asymmetric dependence relationship. These characteristics are also found in crude oil and refined product markets (Hammoudeh et al., 2003; Grégoire et al., 2008; Chang et al., 2010; Ji and Fan, 2011; Serra and Gil, 2012; Aloui et al., 2014).

While hedging models that incorporate these characteristics (in particular, the nonlinear and asymmetric dependence relationship between asset returns) lead to better hedging outcomes, they have been limited to the case of single-asset hedging. This is because, when dealing with more than two random variables (i.e., when hedging more than

* Corresponding author.
E-mail address: kunlapath.s@gmail.com (K. Sukcharoen).

[1] Multiproduct hedging involves the use of multiple futures contracts to hedge exposures to price risks in multiple commodities. In this study, crude oil, gasoline, and heating oil futures are used simultaneously to hedge the refining company's exposures to adverse price movements in the crude oil, gasoline, and heating oil spot markets. In contrast, single-product hedging uses a single futures contract to hedge a spot position in a particular commodity market.

http://dx.doi.org/10.1016/j.eneco.2017.07.012
0140-9883/

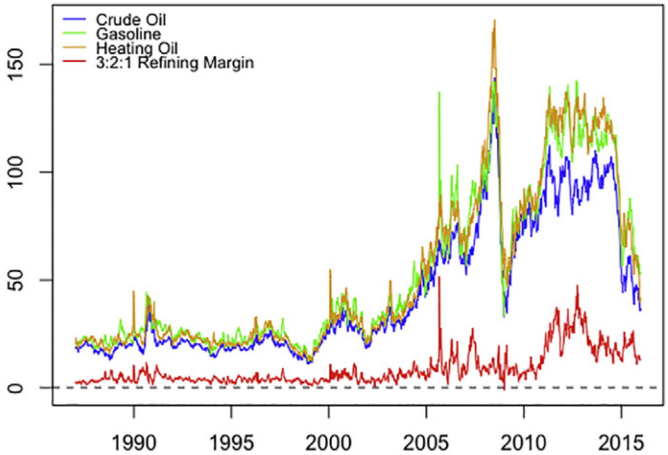

Fig. 1. Weekly crude oil spot prices, gasoline spot prices, heating oil spot prices, and 3:2:1 refining margin (unhedged). Notes: The 3:2:1 refining margin approximates the profitability of a typical U.S. refinery which is able to convert 3 barrels of crude oil to 2 barrels of gasoline and 1 barrel of heating oil.

one asset), standard multivariate copulas are less flexible as they restrict the degree of tail dependence (or comovements during extreme market conditions) between all pairs of variables to be identical. For example, suppose a standard multivariate Archimedean copula is used to model the dependence structure of crude oil, gasoline, and heating oil returns. This means that the degree of tail dependence between crude oil and gasoline returns is assumed to be the same as that between crude oil and heating oil returns and also the same as that between gasoline and heating oil returns. This is clearly too restrictive. Instead of relying on the standard multivariate copulas, one could model the dependence relationship of multiple variables using more advanced multivariate copulas (known as "vine copulas").

The vine copula model, initially introduced by Joe (1996) and first estimated by Kurowicka and Cooke (2006), is a relatively new class of multivariate copula models. Similar to the standard multivariate copula models (e.g., the standard Gaussian, Student's t, and Archimedean copula models), the vine copula model is able to account for both skewness and fat-tailedness in the univariate marginal distributions. This is because the model allows us to separate the modeling of the marginal distributions from the dependence structure that links these marginal distributions to form a joint distribution. However, while the standard copula models require all pairs of variables to have the same tail dependence patterns, the vine copula model permits different tail dependence specifications for different pairs of variables (Czado, 2010; Brechmann and Schepsmeier, 2013). Accordingly, this presents an important opportunity for developing a new multiproduct hedging model that is able to capture the potentially complex (nonlinear, asymmetric, and heterogeneous) dependence patterns among multiple petroleum markets. As such, we propose to combine a vine copula model with Monte Carlo simulation to construct the joint distribution of spot and futures price changes.[2]

In particular, the proposed hedging model builds the joint distribution of multiple variables using an empirical distribution function for the marginal distributions and two different classes of vine copulas – the canonical (C-) and drawable (D-) vine copulas (Kurowicka and Cooke, 2005) – for the dependence structure. The C– and D-vine copula models are estimated using a sequential maximum likelihood procedure proposed by Aas et al. (2009), and the joint distribution is generated using Monte Carlo simulation. The optimal hedge ratios are then derived through a numerical optimization method for four alternative downside-risk hedging objectives: the minimization of Semivariance (SV), Lower Partial Moment (LPM), Value at Risk (VaR), and Expected Shortfall (ES) of the refinery's hedged margin. The usefulness of the proposed model is evaluated through an extensive out-of-sample hedging exercise. Its performance is also compared with that of the widely used nonparametric method and three standard multivariate copula models (namely, the standard Gaussian, Student's t, and Clayton copula models).[3]

This paper contributes to the literature by estimating multiproduct hedge ratios for oil refineries in a downside-risk framework. Previous studies in this area have mainly focused on deriving either minimum-variance or mean-variance hedge ratios.[4] However, it is well known that the variance is not a proper risk measure when asset returns are non-normal because businesses and investors are only concerned with downside risks but not upside risks (Lien and Tse, 1998; Unser, 2000; Veld and Veld-Merkoulova, 2008). Despite the awareness of the non-normality of asset returns, studies on downside risk hedging in a multi-product setting are still scarce.[5] One of the few studies is Power and Vedenov (2010) who estimate the minimum-LPM hedge ratios for a feedlot operator (whose profit depends on the prices of corn, feeder cattle, and fed cattle) and compare them with the minimum-variance hedge ratios. Another is Awudu et al. (2016) who consider a hedging problem of a corn-based ethanol producer and derive the mean-VaR hedge ratios based on two distributional specifications: multivariate normal and Gaussian copula distributions. The other two studies are Chen et al. (2016) and Liu et al. (2017); the former derives mean-VaR hedge ratios for grain processors using standard multivariate copulas, whereas the later estimates minimum-LPM hedge ratios for oil refineries. This paper also develops a multiproduct hedging model in a downside-risk framework. Similar to Liu et al. (2017), we focus on the oil refining industry. However, we consider four (not just one) alternative measures of downside risk. This allows us to examine the sensitivity of the results vis-à-vis the downside risk measures used. In addition, unlike other studies, this paper analyzes the usefulness of the proposed model through an extensive out-of-sample hedging exercise. The out-of-sample performance of different hedging objectives for the best performing hedging model is also evaluated using various hedging effectiveness measures. Moreover, while the vine copula methodology has been applied to study the dependence structures of financial and asset markets (Allen et al., 2013; Zhang, 2014; Zimmer, 2015), to forecast VaR and ES of financial portfolios (Weiß and Supper, 2013; Brechmann et al., 2014; Zhang et al., 2014), and to analyze asset allocation problems (Low et al., 2013; Riccetti, 2013; Bekiros et al., 2015), this is the first study to examine the use of vine copula approach in the context of hedging downside risk. Our findings would benefit oil refineries (as well as other multiproduct hedgers), and provide a richer understanding of the usefulness of vine copulas in energy risk management.

The remainder of this paper is organized as follows. Section 2 describes a methodology. Section 3 presents data and preliminary analysis. Section 4 reports and discusses the empirical results. Section 5 concludes the paper.

2. Methodology

2.1. Oil Refinery's hedging problem

In the empirical analysis, the stylized problem of a typical oil refinery whose profit depends on the refining margin is considered. We focus on a 3:2:1 refining margin, which approximates the profitability of a typical

[2] Following Haigh and Holt (2002) and Alexander et al. (2013), our hedging analysis is based on the price changes. The reasons for why the price changes should be used instead of the log returns or percentage returns are discussed in Alexander et al. (2013).

[3] The standard Clayton copula model is a commonly used Archimedean copula model due to its ability to capture lower tail dependence among variables.

[4] See, for example, Haigh and Holt (2002), Ji and Fan (2011), and Alexander et al. (2013) for previous studies on multiproduct hedging of an oil refinery.

[5] Non-normality of petroleum prices and returns are documented in many studies such as Hammoudeh et al. (2003), Chang et al. (2010), Ji and Fan (2011).