Energy Economics 63 (2017) 31–40

Contents lists available at ScienceDirect

Energy Economics

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

Is hedging the crack spread no longer all it's cracked up to be?☆,☆☆

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A R T I C L E I N F O

Article history:
Received 11 July 2016
Received in revised form 12 January 2017
Accepted 18 January 2017
Available online 2 February 2017

JEL classification:
C58
G13
G17
Q40
Q41
Q47

Keywords:
Crude oil
Crack spread
Gasoline
Futures
Downside risk
Hedging
Copula
Risk management
Dependence

A B S T R A C T

The traditional approach to hedging the crude oil refining margin (crack spread) adopts a fixed 3:2:1 ratio between the futures positions of crude oil, gasoline, and heating oil. However, hedging the latter in arbitrary proportions might be more effective under some conditions. The paper constructs optimal hedging strategies for both scenarios during the periods of relatively stable and volatile oil prices observed in recent years. Minimization of downside risk (LPM_2) and variance are used as alternative hedging objectives. The joint distribution of spot and futures price log returns is modeled using a kernel copula method. The hedging performance of the constructed strategies is compared using hedging effectiveness, expected profit, and expected shortfall. The results show that allowing for arbitrary proportions in the sizes of futures positions generally achieves a better hedging performance. The advantage becomes particularly important during periods characterized by greater variation of the cross-dependence between the price log returns of individual commodities. In addition, using LPM_2 as a hedging criterion can help hedgers to better track downside risk as well as lead to higher expected profit and lower expected shortfall.

1. Introduction

Between 2014 and 2016, crude oil prices have exhibited unusual behavior, dropping from over \$100 per barrel to below \$40 per barrel in less than two years. During the same time period, prices of both gasoline and heating oil almost halved. Facing such drastic changes in both input and output prices, oil refineries are presented with challenging risk management decisions (Ederington et al., 2011; Kaminski, 2014).

A typical oil refinery's profit margin is tied directly to the price difference between crude oil and refined products, commonly called the crack spread. The most popular crack spread, which approximates the real-world output ratio from the refining process, adopts a 3:2:1 ratio, namely, three barrels of crude oil can be cracked into two barrels of gasoline and one barrel of heating oil (EIA, 2002). Oil refineries can reduce their risk exposures to volatile market prices by hedging the crack spread in the futures market. In 1994, NYMEX launched the crack spread contract, which bundles the purchase of three crude oil futures contract with the sale of two unleaded gasoline futures contract and one heating oil futures contract[1] (with delivery a month later) and makes them a single trade, thus lowering margin costs. A 3:2:1 crack spread futures position can also be created as a synthetic contract by directly trading futures on crude oil, gasolines and heating oil at a fixed 3:2:1 ratio. Even though the crack spread futures has a very low trading

☆ The authors acknowledge partial support from Hatch project TEX0-1-9258.
☆☆ An earlier version of this paper was presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, 2016.
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[1] The heating oil contract traded on the New York Mercantile Exchange has been renamed ultra-low-sulfur-diesel (ULSD) futures after the 2013 April contract, but to keep the terminology and notation consistent, we will use the term heating oil (HO) when referring to both the heating oil contract before April 2013 and the ULSD contract after April 2013.

http://dx.doi.org/10.1016/j.eneco.2017.01.020

volume, the data show that the trading volume in the synthetic 3:2:1 crack spread is pretty high.

However, given the somewhat erratic behavior of spot prices in recent years, the question arises whether hedging individual commodities at a ratio other than 3:2:1 might be more effective. Indeed, Kaminski (2014) explains (p. S4) that: “This [3:2:1 ratio] wasn't a perfect hedge by any definition … The decoupling of the WTI [West Texas Intermediate] prices from the world prices reduced the efficiency of the 3:2:1 hedge and induced many hedgers to switch to Brent futures as the preferred hedging instrument…”. Yet, compared with hedging crude oil, hedging the crack spread has received much less attention in the literature (Mahringer and Prokopczuk, 2015).

In this paper we address the above question by constructing optimal hedging strategies for both cases (fixed 3:2:1 ratio and arbitrary proportions) during periods of both relatively stable and volatile oil prices. The hedging performance of the constructed strategies is compared using several criteria. The key finding of the paper is that allowing deviations from the fixed 3:2:1 ratio improves hedging performance regardless of the criterion used. Furthermore, it appears that the key factor affecting hedging effectiveness is the dependence structure between the spot and futures price log returns.

The rest of the paper is organized as follows. Section 2 discusses the relevant literature. Section 3 outlines the modeling methodology including the hedging framework, our approach to modeling the joint distribution of spot and futures price log returns, as well as risk measures used to evaluate hedging performance. Data and implementation details are presented in Section 4, followed by the discussion of the results in Section 5. Lastly, Section 6 provides the concluding remarks.

2. Literature review

Commodity processing activities always involve multiple commodities and thus exposure to price risk on both the input and output side. Soybean crushers buy soybeans and sell soybean oil and soybean meal, ethanol manufacturing involves purchasing corn and selling ethanol and other output products, oil refineries crack crude oil into petroleum products, and so on. Therefore, commodity processors have to implement multi-commodity hedging strategies.

The literature on hedging has traditionally focused on single-commodity hedging, which does not take into account price co-movements between the input and output commodities. However, Haigh and Holt (2002) point out that the assumption of price independence is unreasonable and often leads to optimal hedge ratios that are different from those suggested by the multi-commodity hedging models in which the covariation between the input and output prices is explicitly accounted for (see also Fackler and McNew, 1993; Peterson and Leuthold, 1987). Several recent papers discuss hedging in a multi-commodity setting. Manfredo et al. (2000) study the hedging problem for a typical soybean crushing complex. They find that incorporating a time-varying covariance matrix into the joint price modeling can improve hedging effectiveness. Efimova and Serletis (2014) and Tejeda and Goodwin (2014) examine, for energy and agricultural commodities respectively, the usefulness of dynamically evolving multivariate GARCH models of conditional volatility. Power and Vedenov (2010) and Power et al. (2013) analyze the multi-commodity hedging problem faced by a feedlot operator who buys feeder cattle, corn, and soybeans and sells fed cattle. The authors suggest that incorporating the dependence structure between commodity prices into the hedging model leads to hedging behavior that is more consistent with the one observed in the marketplace.

The crack spread hedging problem for oil refineries has attracted interest in recent years, partly due to the highly volatile oil market. The North American oil production and refining market has undergone major changes in recent years. According to Kaminski (2014, p. S3) “[the] increase in production of crude in locations such as The Bakken and Eagle Ford, which were a few years ago of marginal importance to the US oil industry … collided with the existing transportation and refining infrastructure. Several congestion points emerged in the transportation grid and this, in turn, resulted in the breakdown of historical price relationships …”

Haigh and Holt (2002) show that accounting for time variation in the relationship between energy price series (crude oil, gasoline and heating oil) yields substantial rewards to hedgers in terms of risk reduction. Ji and Fan (2011) adopt a dynamic hedging approach for refineries and find that considering the interaction between different product markets as well as variation in price behavior over time can lead to a better multiproduct hedging strategy.

Various multivariate modeling methods as well as risk measures have been used to determine optimal hedging strategies and to analyze their performance. Variance of the effective net price or revenue continues to be the most commonly used measure of risk in the hedging literature, with variance minimization being the hedging objective. For example, Awudu et al. (2016) compare different hedging strategies for an ethanol producer using a Mean-VaR framework. However, looking at the crack spread find Alexander et al. (2013) find that variance-minimizing hedges offer no improvement in risk reduction. Indeed, Lien and Tse (2002) argue that a one-sided risk measure is closer to commodity hedgers' risk objective than the traditional variance measure. This is because upside and downside deviations are not equally undesirable in risk management. In that spirit, several recent papers use the second-order lower partial moment (LPM_2) as an alternative to variance (for example, Demirer and Lien, 2003; Turvey and Nayak, 2003; Mattos et al., 2008; Power and Vedenov, 2010).

Naturally, using different risk measures leads to different hedging strategies. Mattos et al. (2008) find that when transaction costs and alternative investments are introduced, the adoption of a downside risk measure with low reference levels can lead to hedge ratios that differ substantially from the minimum-variance hedge ratios. Power and Vedenov (2010) find that minimizing the LPM_2 measure results in smaller optimal hedge ratios compared to the minimum variance hedge. Furthermore, they suggest that the optimal hedge ratios implied by the downside risk criterion are more consistent with the behavior observed in the marketplace. In order to account for possibility of different hedging objectives, in this paper, we construct optimal hedging strategies using both variance minimization (MV) and LPM_2 minimization as hedging criteria.

Another important issue in the analysis of multi-commodity hedging is how to model the joint distribution of prices or returns. Multivariate normality of returns is often assumed for reasons of convenience. However, the distributions of spot and futures price log returns are known to deviate from normality (e.g. Ederington et al., 2011; Lai, 2012). Several methods have been suggested in the literature to circumvent this issue. For example, Manfredo et al. (2000) estimate a time-varying covariance matrix and a MGARCH(1,1) model with a constant correlation matrix. Power and Vedenov (2010) use a kernel copula approach to model the joint distribution of spot and futures price returns in a multi-commodity setting. The kernel copula methodology is non-parametric and imposes minimum assumptions about the underlying distribution. Tong et al. (2013) use thirteen parametric copula models with different underlying assumptions on the dependence structures to estimate the co-movement between crude oil and petroleum product prices. Power et al. (2013) propose a Nonparametric Copula-based Generalized Autoregressive Conditional Heteroskedastic (NPC-GARCH) dynamic hedging approach and find that it better captures lower tail risk than do other models such as GARCH-DCC or GARCH-BEKK. In this paper, we follow Power and Vedenov (2010) and use a kernel copula approach to model the joint distribution of spot and futures price log returns. This allows us to move away from the multivariate normality assumption and better reproduce both the individual and joint behavior of price series.

The contribution of this paper can be described in the context of the prior literature. Although research on futures hedging is vast, there are