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Futures hedging effectiveness under the segmentation of bear/bull energy markets

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ABSTRACT

This article undertakes eight hedging models (Regression, MD-GARCH, BEKK-GARCH, CCC-GARCH, ECM-MD, ECM-BEKK, ECM-CCC, and state space models) to investigate hedging effectiveness of different price scenarios in energy futures markets. Different models have systematically evidenced that hedging effectiveness is higher in an increasing pattern (termed "bull markets") than in a decreasing pattern (termed "bear markets") for crude oil and gasoline futures. That is, findings show asymmetric hedging performance between upward and downward price trends consistently from the most popular hedging models in literature. Out-of-sample examination also suggests that the ranking of hedging effectiveness of different hedging models is not parallel in different price patterns across futures contracts, implying that investors should adjust their hedging strategies accordingly.

1. Introduction

Borrowing the concepts of a filter discipline by Alexander (1961, 1964), Fama and Blume (1966), and Sweeney (1988), this work segmented the hedging horizon based on upward and downward price trends, termed bull and bear markets, to investigate futures hedging performance in each sub-period for various econometric models broadly adopted in hedging literature. The result surprisingly reveals systematically different hedging effectiveness in the two price–trend scenarios across models and futures contracts.

Current energy price movements are highly linked to the world economy. This is because energy prices increasingly affect business profitability across industries due to their strong reliance on petroleum-based products. Prices for most petroleum-based commodities have more than doubled since the end of 2003 and presently continue to remain at high levels. In the first half-year of 2008, U.S. crude oil price soared to settle above 145 US dollars a barrel on the New York Mercantile Exchange, and the price of crude oil futures also jumped to 147.27 US dollars in July, 2008. Different from the previous high oil price caused by a sudden embargo or a supply cut-offs, the recent persistently high price is tied to the increasing demand for oil from fast-growing developing nations like China and India. Next to the weak dollar, speculation on commodity markets also plays a crucial role in the oil price surge. According to the Commodity Futures Trading Commission (CFTC) in 2008, the percentage of trading volumes attributed to speculation has increased from 37% in 2000 to 70% in 2008 (Brocato, 2008). A prevailing concern is the high possibility that if speculative funds flooding the commodity markets move into and out of energy markets, oil prices will go higher, making the market even more volatile. This corresponds to a recent finding of Jalali-Naini and Manesh (2006) that energy prices are typically characterized by high volatility. To mitigate the adverse impact of energy price fluctuations, business and investors are always searching for effective ways to hedge energy price risks. Among other strategies, an investor facing volatile price movements in spot markets could reduce uncertainty by simultaneously holding an opposite futures position on underlying assets.

A critical factor for successful price risk reduction of futures trading is whether or not the hedging strategy is capable of capturing the dynamics between futures and its underlying spot prices. Two separate but equally important literature findings motivate this study. First, empirical studies have frequently found a negative relationship between oil prices and real activity (Hamilton, 1983; Burbidge and Harrison, 1984; Gisser and Goodwin, 1986; Mork, 1989; and Hamilton, 1996; Jones et al., 2004; Barsky and Kilian, 2004; Jiménez-Rodríguez and Sánchez, 2005; Aguiar-Conraria and Wen, 2007; Bollino, 2007). Secondly, the literature has demonstrated that asset price behaviors work differently under differing trend patterns. Meneu and Torro (2003) find that shock impact on stock futures markets takes a long time to subside in a bear market, while the

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impact in a bull market diminishes quickly. These asymmetric effects in upward and downward price patterns may further cause different co-movement behaviors or conditional covariance between spot and futures prices between upward and downward trends. A preliminary test of unconditional correlations between the two serials for crude oil and gasoline in this study provide evidence for this argument (in Section 3.2).

This paper assumes a representative hedger who demands crude oil/gasoline. Facing uncertain commodity prices, the hedger who buys crude oil/gasoline futures contracts seeks for a steady return from asset holding. Constructing a hedged portfolio should include an appropriate hedging ratio, defined as the size of the futures position to the size of spot exposure. Much literature focuses on identifying the most effective hedging ratio through various econometric models with different estimation procedures and with data from various commodity futures (Baillie and Myers, 1991; Myers, 1991; Bera et al. 1997; Moschini and Myers, 2002; Bystrom, 2003). These approaches can be roughly classified into two categories: a traditional pure hedge and a minimum-variance hedge. The former method assumes one hedge ratio, which does not work well in empirical applications because the overly simple strategy fails to account for basis risks.

The minimum-variance hedge first introduced by Johnson (1960) is, by definition, a strategy that minimizes hedged portfolio risks. The "optimal" hedge ratio (OHR) is one that meets the hedging objective. Under the mean-variance framework of Markowitz (1952) and the martingale assumption, the OHR can be denoted as a ratio of covariance between cash and futures returns to the variance of futures returns. Stein (1961) and Ederington (1979) suggest obtaining the OHR by regressing spot returns against futures returns. This simple procedure is widely adopted in later studies (Myers, 1991; Kroner and Sultan, 1993; Thomas and Brooks, 2001; Lee et al., 2006). One of the major problems with the simple regression model estimated by the OLS method first raised by Myers (1991), however, is the presumed constant hedging ratio. Myers (1991) argues that if the joint distribution of futures and spot prices are time-varying in the sense that their second moments may change over time, a dynamic OHR presumably is expected. The GARCH model which has been proved to be successful in capturing heteroskedasticity and clustering volatility of financial variables is well suited to solve the problem. An earlier study by Baillie and Myers (1991), using a multivariate GARCH model, documents superior hedging effectiveness in the US agricultural commodities market.

This strand of literature in multivariate GARCH models has made great efforts on specifying the variance–covariance matrix of the random process. The constant conditional correlation GARCH (CCC-GARCH) model first proposed by Bollerslev (1990) is one of the most popular specifications in early studies due to its ease of model estimation. Nevertheless, assuming a constant correlation between futures and spot returns seems too restrictive. Allowing for time-varying correlations, the Matrix-Diagonal (MD) GARCH model used by Ding(1994) and Bollerslev et al. (1994), and the BEKK-GARCH model first presented by Engle and Kroner (1995), have obtained much attention in the literature. These models meet the requirement that their variance–covariance matrices are guaranteed to be positive semi-definite (PSD) and have been extensively employed in more recent studies (Bera et al., 1997; Haigh and Holt, 2002; Lien et al., 2002; Bystrom, 2003; Lee et al., 2006).

Empirical results of hedging effectiveness across the aforementioned models, however, are mixed. Gagnon and Lypny (1995) and Lynpy and Powalla (1998) demonstrate that hedging behavior is more effective using the BEKK-GARCH model than using the OLS regression for stock index and interest rate, while Bera et al. (1997) find the opposite result for commodity futures. Chakraborty and Barkoulas (1999) and Lien et al. (2002) reach a similar conclusion that OLS regression is superior to the BEKK-GARCH model in hedging performance for stock indexes, currencies and commodities.

With advances in time–series models, Granger (1983) proposes a concept of co-integration to capture the long-term equilibrium relationship among non-stationary variables applicable to movements between cash and futures prices in hedging models. An error correction model (ECM) explicitly specifies this co-integration effect. Chou et al. (1996) verifies that an ECM improves hedging effectiveness. Kroner and Sultan (1993), Park and Switzer (1995), and Lypny and Powalla (1998) arrive at an opposite conclusion.

The state space model opposes static estimations of traditional regressions and represents another stream of estimation procedures in econometrics, allowing for a non-constant value in mean (Harvey, 1989; Hamilton, 1994, and Durbin and Koopman, 2001). The state space model approach, a recursive solution of moments through implementing a predictor–corrector estimator suggested by Kalman (1960), is one of the most popular methods among others. Schwartz (1997) uses this approach to mimic price behavior in futures markets, but it has yet to be empirically applied to hedging studies.

Given the theoretical pros and cons among the hedging models discussed above and the mixed empirical results of their hedging performance, this study considered a complete list of these eight models, including Regression, MD-GARCH, BEKK-GARCH, CCC-GARCH, ECM-MD, ECM-BEKK, ECM-CCC, and state space models. The absence of such a comparison in the energy markets in literature provides one more contribution to our study. Empirical results of this study, including in-sample and out-of-sample analysis, reveal new evidence that hedging effectiveness during bull and bear futures markets is systematically different across econometric models and commodities.

This article is composed of five sections. Section one addresses the importance of risk management in energy markets and briefly reviews the hedging literature. Section two introduces theoretical models in hedging decision-making and the measurement of hedging effectiveness. Section three includes preliminary analysis of energy spot and futures data. Section four reports empirical evidence for both in-sample and out-of-sample hedging performance in bull and bear market scenarios. Section five presents the conclusions.

2. Hedging strategy and methodology

This section reviews a variety of hedging models, starting with the conventional regression model. By relaxing restrictions on the regression model, this work constructs a list of seven other econometric models, organized into three categories. The first category consists of the multivariate GARCH-family models, including the MD-GARCH, BEKK-GARCH, and CCC-GARCH models. The second category is composed of the Error Correction models, consisting of the ECM-MD, ECM-BEKK and ECM-CCC models. The third category is the state space model. As most hedging studies, we ignore transaction costs to simplify the estimation process. The last part of this section presents the hedging performance measure to gauge the effectiveness of different hedging techniques.

2.1. Hedging strategy

The mean-variance (MV) hedge ratio first introduced by Johnson (1960), Stein (1961) and Ederington (1979) defines the optimal hedge ratio as minimizing hedged portfolio variance. Let RS_t and RF_t represent spot and futures returns at a given time t, respectively, the optimal hedge ratio of h is as follows:

$$h = \frac{\sigma_{sf}}{\sigma_f^2} = \rho \times \frac{\sigma_s}{\sigma_f} \tag{1}$$

where σ_{sf} denotes the covariance of RS_t and RF_t, and σ_f^2 are the variance of RF_t; ρ, σ_s, and σ_f represent the correlation coefficient and standard deviation of spot and futures returns, respectively.