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Downside risk and the energy hedger's horizon

Thomas Conlon [1], John Cotter *

Smurfit School of Business, University College Dublin, Carysfort Avenue, Blackrock, Co. Dublin, Ireland

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ABSTRACT

In this paper, we explore the impact of investor time-horizon on an optimal downside hedged energy portfolio. The optimal heating oil hedge ratio is first calculated for a variety of downside risk objective functions at different time-horizons using the wavelet transform. Next, associated hedging effectiveness is contrasted for a range of risk metrics, with all metrics showing increasing hedging effectiveness at longer horizons. Moreover, decreased hedging effectiveness is demonstrated for increased levels of uncertainty at higher confidence intervals. While small differences in effectiveness are found across the different hedging objectives, time-horizon effects are found to dominate confirming the importance of the hedging horizon. The findings suggest that while downside risk measures are useful in determining an optimal futures hedge encompassing negative returns, hedging horizon and confidence intervals should also be given careful consideration by the energy hedger.

1. Introduction

The practice of risk management often involves the use of futures contracts to manage the price risk associated with a given spot market position. The optimal futures hedge ratio necessary to reduce the risk associated with a given spot position is commonly determined using variants of the minimum-variance approach (Brooks et al., 2002; Chen et al., 2003). However, the minimum-variance approach treats positive and negative fluctuations equally, while hedgers may prioritize the reduction of downside risk only Hung and Lee, 2007. Another important hedging consideration is the horizon over which a hedger wishes to reduce risk, with improved effectiveness found for longer horizons (Ederington, 1979). However, these and other studies have only considered the impact of the hedging horizon on the minimum-variance hedge ratio (for example, In and Kim, 2006). In this study, we build on the previous literature by considering the effect of the hedging horizon on both the optimal futures hedge ratio and associated effectiveness for a variety of downside risk hedging objectives.

The primary aim of corporate risk management is to provide protection against the possibility of dangerous tail-risk events (Stulz, 1996). In the context of futures hedging, a range of alternative downside risk measures have been proposed to estimate and subsequently limit the impact of low probability tail-risk events.[2] Value-at-risk (VaR) and conditional value-at-risk (CVaR or expected shortfall) are two approaches to measure potential loss of a portfolio over a given period[3] and have been applied as risk objectives in a portfolio allocation setting (Adam et al., 2008). In recent research VaR and CVaR have also been adopted for use as the hedging risk objective function. Using VaR and CVaR as the measure of hedge portfolio risk, Chang (2011) and Harris and Shen (2006) determined the optimal futures hedge ratio required to minimize the tail risk of the hedge portfolio. An alternative downside risk measure often applied in the literature is the semivariance, which measures the expected value of deviations below a target value. The semivariance may also be applied to calculate the optimal hedge ratio necessary to reduce the semivariance risk of a spot position hedged by futures (Turvey and Nayak, 2003). In this paper, we move beyond the minimum-variance framework to consider the impact of the energy hedging horizon and the investor confidence investor on differing risk objective functions including value-at-risk, conditional value-at-risk and semivariance.

Given the range of alternative risk objective functions available to energy futures hedgers, it is important to understand their

* Corresponding author. Tel.: +353 17168900.
E-mail addresses: conlon.thomas@ucd.ie (T. Conlon), john.cotter@ucd.ie (J. Cotter).
1 Tel.: +353 17168909.

2 A thorough review of the different objective functions applied to minimize risk in futures hedging can be found in Chen et al. (2003). Recent studies have also examined the impact of investor preferences such as risk aversion on the optimal hedging strategy, finding significant variation from risk minimization strategies (Cotter and Hanly, 2010, 2012).

3 Additional details and applications of both VaR and CVaR can be found in Basak and Shapiro (2001) and Bertsimas et al. (2004).

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performance for different hedging horizons. The effectiveness of a standard minimum-variance energy hedge has been explored using a variety of performance metrics, including variance, semi-variance, VaR and CVaR. Further, performance of downside objective functions has been assessed using a spectrum of performance measures (Harris and Shen, 2006). However, previous studies have only evaluated downside effectiveness from the perspective of an investor considering a single confidence level. In this study, we expand futures hedging performance measurement to incorporate a range of confidence intervals at different hedging horizons.

Earlier studies considered data sampled at weekly, fortnightly and monthly horizons to demonstrate an increase in variance reduction effectiveness for hedgers at longer horizons (Benet, 1992; Ederington, 1979). However, Benet, (1992) found a lack of stability in the effectiveness at longer horizons out-of-sample, due to the sample reduction problem. To overcome the problem of reduced data at longer horizons, wavelet multiscaling techniques have been adopted.[4] Applying a minimum-variance framework, In and Kim, (2006) demonstrated that S&P index hedgers achieve greater effectiveness at longer horizons. Examining a wide range of futures contracts, Lien and Shrestha (2007) showed both increased hedge ratios and out-of-sample effectiveness in the case of a minimum-variance hedger for increasing horizon. Finally, Conlon and Cotter (2012) applied a minimum-variance framework to introduce a dynamic time and horizon dependent futures hedge ratio. This article differs from the above by examining a number of downside hedging metrics in a multi-horizon framework. In particular, while Conlon and Cotter (2012) measure the effectiveness of a minimum-variance hedge ratio using downside risk measures, in this paper we consider downside risk measures as both the hedging objective function and for the measurement of effectiveness at different horizons. This approach allows a consistent view of the hedger's preferences to be applied to both risk management and measurement.

This paper makes a number of contributions to the literature. First, in the case of energy hedging, we demonstrate a decrease in hedging effectiveness for increased levels of risk uncertainty at all hedging horizons. Further, we build upon the previous application of minimum-variance wavelet futures hedging, by investigating the impact of different downside risk objective functions at different horizons. Our results indicate an increase in the optimal heating oil hedge ratio and improved effectiveness at longer horizons, regardless of the objective function used to minimize hedge portfolio risk. While small differences in effectiveness are found across the different hedging objectives, time-horizon effects are found to dominate confirming the importance of considering the hedger's horizon. The findings suggest that while downside risk measures are useful in the computation of an optimal hedge ratio that accounts for unwanted negative returns, the hedging horizon and confidence intervals should also be given careful consideration by the hedger.

This remainder of this paper is structured as follows: Section 2 introduces the wavelet multiscaling technique and outlines the different objective functions examined. In Section 3, the empirical energy data and their properties are outlined. Section 4 discusses the empirical findings, while conclusions are given in Section 5.

[4] The wavelet transform has been applied to a range of problems in economics and finance, including the characteristics of international diversification at differing horizons (Rua and Nunes, 2009), the relationship between stock returns and inflation for various horizons (Kim and In, 2005), the determination of the beta of a stock and the expected returns at varying horizons (Gençay et al., 2003, 2005) and the flow of information between horizon dependent volatilities (Gençay et al., 2010). Moreover, wavelets have been applied to separate short-term noise and long term trends in crude oil prices (de Souza e Silva et al., 2010; Naccache, 2011). Further details on wavelet multiscaling can be found in Gençay et al. (2001).

2. Methodology

In determining the optimal hedge ratio necessary to reduce the risk associated with a given spot position, market participants need to consider preferences related to hedging horizon and risk objective. In this section, we introduce wavelet multiscaling techniques to understand the behavior of financial time-series at different horizons and then consider a variety of alternative hedging objective functions including the downside metrics value-at-risk, conditional value-at-risk and semivariance.

2.1. Wavelet analysis

Here, we provide a brief introduction into the application of wavelet multiscaling techniques to the time-horizon decomposition of financial time-series.[5] Wavelets can be interpreted as 'small waves' with limited duration and are capable of decomposing a time-series in both time and frequency. By incorporating information from all available data at different horizons, wavelets overcome the problem of reduced data at longer horizons. Wavelet analysis can be considered a generalization of the Fourier transform, which employs harmonic functions as a basis, characterized by frequency. While the wavelet transform also uses oscillatory functions, in contrast to the Fourier transform these decay rapidly to zero. The family of functions generated using the wavelet transform are dilations and transformations of a single function, the mother wavelet, providing self-similarity. This can be distinguished from the windowed Fourier transform, where the frequency, width and position of the window are all independent. The wavelet transform is particularly suitable for financial data, due to the ability to accurately capture high frequency, high amplitude events such as spikes in returns, to decompose non-stationary data and also, due to self-similarity properties.

The discrete wavelet transform (DWT) provides an efficient means of studying the multiresolution properties of a signal, allowing decomposition into different time-horizons or frequency components (Gençay et al., 2001; Percival and Walden, 2000). The DWT consists of two basic wavelet functions, the father ϕ and mother ψ wavelets, given by:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi\left(2^{j}t-k\right) \tag{1}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(2^{j}t-k\right) \tag{2}$$

where $j=1,\ldots J$ in a J-level decomposition and k is a translation parameter. The father wavelet integrates to one and reconstructs the longest time-scale component of the series, (the trend), while the mother wavelet integrates to zero and is used to describe deviations from the trend. It is possible to show that a discrete signal $f(t)$ can be decomposed as a sequence of projections onto the father and mother wavelets. In particular, the orthogonal wavelet series approximates a continuous signal $f(t)$ as

$$f(t)\approx\sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{3}$$

where J is the number of multiresolution levels (or *scales*) and k ranges from 1 to the number of coefficients in the specified level. The coefficients $s_{J,k}$ and $d_{j,k}$ are the wavelet transform coefficients, while $\phi_{J,k}$ and $\psi_{j,k}$ are the approximating wavelet functions, where coefficients from level $j=1\ldots J$ are associated with scale $[2^{j-1},2^{j}]$.

In this paper, we apply an extended version of the DWT, the maximum overlap discrete wavelet transform (MODWT), a variation of the orthogonal discrete wavelet transform (Percival and Walden, 2000). The MODWT is considered preferable to the DWT as it is

[5] Readers are referred to Gençay et al. (2001), In and Kim (2006), and Percival and Walden (2000) for further technical detail.