Contribution of Exchange Traded Funds in Hedging Crude Oil Price Risk

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ABSTRACT
In this study, we empirically analyze the contributions of three crude oil-based exchange traded funds (ETFs) and the futures contract in hedging crude oil price risk. In order to measure hedging contributions of ETFs, we estimate the usual minimum variance hedge ratios as well as the quantile based minimum variance hedge ratios based on three different methods. We also compute the hedging effectiveness of the futures contract and three ETFs. We find that ETFs can be used as hedging instruments especially for the longer hedging horizons and extreme quantiles. However, overall, we find the futures contract to be the most effective instrument for hedging.

KEYWORDS
Price Discovery, Information Share, Quantile Hedge Ratio, Exchange Traded Funds

JEL Classifications: C3, G1, Q4

INTRODUCTION

Due to the importance of energy on many aspects of national and international economies, the behavior of energy price, like crude oil price, has received a significant amount of attention from academicians, practitioners as well as policy makers.[1] There are many studies that analyze the relationship between oil price and macroeconomic variables (e.g., Jones and Kaul, 1996; Driesprong et al., 2008; Basher et al., 2012; Ji, 2012; McCarthy and Orlov, 2012; Asteriou and Bashmakova, 2013; Sim and Zhou, 2015; Gatfaoui, 2016; Kyrtsou et al., 2016; Hatemi-J et al., 2017). Some other studies analyze the relation between oil price and stock market (e.g., Papapetrou, 2001; Cunado and Perez de Gracia, 2003; Kilian, 2009; Chiang et al., 2015; D'Ecclesia, 2016; Christoffersen and Pan, 2018). The connection between the crude oil and stock market has been stronger over the past decade due to the increased participation from financial commodity investors. This is a situation referred to as the "financialization of commodity markets," which has also contributed to the creation of oil-based ETFs (Tang and Xiong, 2012; Cheng and Xiong, 2014; Henderson et al., 2015). Oil based ETFs are essentially managed funds that trade like shares (NYSE, 2017). These funds replicate the performance of crude oil through the acquisition of oil-related securities. The creation of oil-based ETFs lowers the barriers for financial commodity investors to participate in the crude oil market. Therefore, oil-based ETFs could be used for hedging crude oil price risk.

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[1] 1There is a special issue of Journal of Banking & Finance focused on commodity and energy markets (Journal of Banking & Finance, volume 95, 2018). This highlights the importance of energy as an important asset class.

To the best of our knowledge, there are very few studies that analyze the hedging contribution of energy-based ETFs. Murdock and Richie (2008) use one of the ETFs (USO) considered in this study and analyze the correlations among crude oil spot, futures (with two different maturities) and USO prices using daily closing data from July 2005 to July 2008. They also analyze correlations among price changes. They find that oil ETF is not an effective instrument to hedge against the change in crude oil price as compared to the futures contracts. However, Murdock and Richie (2008) do not estimate the hedge ratio, nor do they test the hedging effectiveness directly. In another study, Sukcharoen et al., (2015) analyze the hedging effectiveness of gasoline-based ETFs. They find that, in terms of variance reduction, the static OLS and VEC/VAR models are the best hedging strategies. In this study, we estimate the hedge ratio using three different methods, two of which incorporates the cointegrating relation between the crude oil spot price and the price of the hedging instrument. Furthermore, Lien et al. (2016) and Shrestha et al. (2018) show that hedge ratios can be different at different quantiles of the distribution, and they suggest to use quantile hedge ratios to take care of these differences. Therefore, we also estimate the quantile hedge ratios in this study. Finally, we compute the hedging effectiveness for all the hedging instruments used in the study, which include futures contract and three ETFs.

In this study, we use daily data from January 4, 2010 to December 29, 2017 obtained from Datastream.[2] The five price series used in this study include crude oil spot (WTI spot Cushing) and near month crude oil futures while the three ETFs includes USO (United States Oil Fund), OIL (iPath S&P GSCI Crude Oil), and USL (United States 12 Month Oil Fund).[3] Oil ETF is found to have the lowest hedge ratio, followed by futures, USO and USL. We find that the hedging effectiveness of the futures contract is the highest, followed by USO, OIL and USL. The hedging effectiveness over all quantiles improves for all instruments (e.g., futures and three ETFs) as the hedging horizon is increased from 1-day to 4-week. It is interesting to note that the hedging effectiveness of USO at both extreme quantiles is close to that of futures contract. However, for the middle quantiles the hedging effectiveness of USO is significantly lower compared to the futures contract. Therefore, we conclude that ETFs can also play an important role in hedging crude oil price risk.

We contribute to the literature in several ways. Firstly, we extend the findings of Murdock and Richie (2008) by actually computing the hedge ratios. Secondly, we compute minimum variance hedge ratio based on three methods: (i) OLS, (ii) error-correction based OLS (ECM-OLS) and (iii) error-correction based dynamic OLS (ECM-DOLS). Thirdly, we also compute quantile-based hedge ratios in order to analyze if the hedge ratio depends on quantiles. Fourthly, we compute hedging effectiveness of hedge ratios based on three different methods. Finally, we analyze hedge ratio and their effectiveness for daily, weekly and 4-weekly data so see the effect of hedging horizon on hedge ratio as well as the hedging effectiveness.

The remainder of this paper is as follows. The next section will discuss the methodology used in this paper and Section 3 presents the empirical results. The paper concludes in Section 4.

METHODOLOGY

In this section, we briefly describe the methods used to estimate the *minimum variance (MV)* ratios using different models based on Lien et al., (2016). We use three different versions of OLS model:

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[2] We use daily instead of intraday price because the spot market does not seem to change too frequently during the day. The lack of movements in the intraday spot price would compromise the intraday price discovery analysis.

[3] Our study only includes three oil-based ETFs that mimic the movements of WTI Cushing crude oil price by investing in the nearby month futures. We exclude oil ETFs that have share ownership in oil-related companies as well as ETFs that engage in leverage strategies. The exclusions allow us to capture a clean price discovery contribution of the oil ETFs that are not influenced by firm-specific or leverage risks.

(i) OLS, (ii) OLS with error-correction (ECM-OLS) and (iii) dynamic OLS with error-correction (ECM-DOLS). We also estimate each of the three models using quantile regression method.

OLS ESTIMATION OF THE OPTIMAL HEDGE RATIO

Let s_t and g_t represent the natural logarithm of the spot price and the price of a hedging instrument, which could be the futures contract or one of the ETFs, at time t. Therefore, returns on spot and hedging instrument positions can be defined as $\Delta s_t = s_t - s_{t-1}$ and $\Delta g_t = g_t - g_{t-1}$ respectively. Then, the return on the hedged portfolio (R_H) is given by,

$$R_H = \Delta s_t - H\Delta g_t \qquad (1)$$

where *H* is the so-called hedge ratio.

The *MV* hedge ratio H_{MV} is obtained by minimizing the variance of R_H with respect to *H* and is given by:

$$H_{MV} = \frac{Cov(\Delta s_t, \Delta g_t)}{Var(\Delta g_t)} \qquad (2)$$

Using the OLS method, the *MV* hedge ratio mentioned above can be estimated from the following regression equation:

$$\Delta s_t = a + \beta\Delta g_t + e_t \qquad (3)$$

where the estimate of the *MV* hedge ratio is given by the estimate of the slope coefficient, β. The estimation method, where the optimal hedge ratio is obtained by estimating equation (3) using OLS, is referred to as OLS method.

However, the spot price and the price of the hedging instrument are expected to be unit-root process where these two-price series are expected to be cointegrated.[4] Then, in the presence of cointegrating relation between the two prices, regression equation (3) will be mis specified (Engle and Granger, 1987). In this case, the correct model to use is the following error correction model (ECM):

$$\Delta s_t = \alpha + \beta\Delta g_t + \gamma u_{t-1} + \sum_{i=1}^{m} \emptyset_{s_i}\Delta s_{t-i} + \sum_{j=1}^{n} \emptyset_{g_j}\Delta g_{t-j} + \varepsilon_t \qquad (4)$$

where u_t is the residual from the cointegrating regression given by:

$$s_t = a + bg_t + u_t \qquad (5)$$

The estimate of the ECM based *MN* hedge ratio is given by the estimate of β in equation (4). The orders of the lags in Δs_t and Δg_t in equation (4), can be determined by using the Akaike information criterion (AIC) (Akaike, 1973). In general, the cointegrating regression (equation (5)) is estimated using the OLS method. This method of estimating the optimal hedge ratio is referred to as ECM-OLS method. However, when estimating the cointegrating regression, a dynamic OLS or DOLS (Stock and Watson, 1993) can have better statistical properties compared to OLS. Therefore, we also use DOLS to estimate

[4] In efficient markets, the logarithm of prices are expected to follow a random walk process so that the returns (the differences in logarithm of prices), which represents returns, are independent. This hypothesis of uni-root is also known as *martingale hypothesis* (Fama, 1970; LeRoy, 1973, 1989).

cointegrating regression (equation (5)) and use the residual from this regression in equation (4) to estimate the MV hedge ratio.[5] This method is referred to as ECM-DOLS method.

QUANTILE ESTIMATION OF OPTIMAL HEDGE RATIO

The conventional *MV* hedge ratios described above are estimated using expected values of the distribution. However the hedge ratio can be different at different quantiles of the distribution. Therefore, following Lien et al. (2016) and Shrestha et al. (2018), we also estimate the quantile hedge ratios to see if the hedge ratio depends on the quantile of the distribution. Here we briefly describe the estimation of quantile hedge ratio.

As discussed above, the OLS, ECM-OLS and ECM-DOLS method of estimating *MV* hedge ratio use equations (3) or (4). However, the quantile hedge ratios are obtained by estimating the same equations but using a quantile regression method. The quantile regression is a semi-parametric regression method which was introduced by Koenker and Bassett (1978) aiming to find relations between each of the quantiles of the conditional distribution of the response variable and the observed covariates. In this section, we provide a brief discussion on the quantile regression.

First, let us look at the OLS estimator of the model (3).[6] Let us represent the samples of returns on spot and hedging instrument as follows:

$$y_t = \Delta s_t, t = 1,\ldots,T \; \& \; x_t = \Delta g_t, t = 1,\ldots,T$$

Then, the OLS estimator of the parameter vector $[\alpha, \beta]$ can be obtained as

$$\left[\hat{\alpha}, \hat{\beta}\right] = \underset{\alpha,\beta}{arg\,min} \sum_{t=1}^{T}[y_t - \mu_t(x_t;\alpha,\beta)]^2, \;\; \mu_t(x_t;\alpha,\beta) = \alpha + \beta x_t \quad (6)$$

where the estimated function $\mu(\;)$ is the sample estimator of the conditional expectation function under the linear model, $E(y_t|x_t) = \mu_t(x_t;\alpha,\beta) = \alpha + \beta x_t$. Therefore, the OLS estimator depends on the average relation between y_t and x_t. Now, let us look at the conditional quantile function and the associated parameter vector. Let *Y* be a real-valued random variable with continuous cumulative distribution function $F_Y(y) = P(Y \leq y)$. The $\tau - th$ quantile of *Y* is given by:

$$q(\tau) = F_Y^{-1}(\tau) = inf\{y: F_Y(y) \geq \tau\} \quad (7)$$

where $\tau \in [0, 1]$

If we define the loss function as $\rho_\tau(y) = y\big(\tau - I(y < 0)\big)$, a specific quantile can be formulated as the solution to a minimization problem (e.g. Koenker, & Bassett, 1978) that minimizes the expected loss of *Y – u* with respect to *u*:

$$\begin{aligned} q(\tau) &= \underset{u}{arg\,min}\, E\big(\rho_\tau(Y-u)\big) \\ &= \underset{u}{arg\,min}\left[(\tau - 1)\int_{-\infty}^{u}(y-u)dF_y(y) + \tau\int_{u}^{\infty}(y-u)dF_Y(y)\right] \end{aligned} \quad (8)$$

where $q(\tau)$ is $\tau - th$ quantile of the random variable $Y: F_Y(q_\tau) = \tau$.

[5] In the case of DOLS, the following regression equation is estimated instead of equation (4).
$s_t = a + bg_t + \sum_{i=-p}^{+q} c_i \Delta g_{t-i} + e_t$

[6] Similar interpretation applies to the ECM model (4).

Solving the sample analogue gives the estimator of quantile (q_τ). Based on the linear model (3), we can represent the $\tau - th$ conditional quantile function as $q_{y_t|x_t}(\tau) = \alpha(\tau) + \beta(\tau)x_t$. Given the distribution function of y_t, the parameter vector $[\alpha(\tau)\beta(\tau)]$ can be obtained by solving:

$$[\alpha(\tau)\beta(\tau)] = \underset{\alpha(\tau)\beta(\tau)}{arg\ min}\ L\big(\alpha(\tau), \beta(\tau)\big) = \underset{\alpha(\tau)\beta(\tau)}{arg\ min}\ E[\rho_\tau(y_\tau - \alpha(\tau) - \beta(\tau)x_t)] \tag{9}$$

where the expected loss function value, $L\big(\alpha(\tau), \beta(\tau)\big)$, is equal to $E[\rho_\tau(y_\tau - \alpha(\tau) - \beta(\tau)x_t)]$. $\beta(\tau)$ is referred to as the quantile hedge ratio at quantile τ.[7] The estimator of the parameter vector $[\alpha(\tau)\beta(\tau)]$ can be found by solving the sample analogue:

$$[\hat{\alpha}\ (\tau), \hat{\beta}\ (\tau)] = \underset{\alpha(\tau)\beta(\tau)}{arg\ min}\ L_S\big(\alpha(\tau), \beta(\tau)\big) = \underset{\alpha(\tau)\beta(\tau)}{arg\ min}\ \textstyle\sum_{t=1}^{T}[\rho_\tau(y_t - \alpha(\tau) - \beta(\tau)x_t)] \tag{10}$$

where the sample loss function, $L_S\big(\alpha(\tau), \beta(\tau)\big)$, is given by,

$$L_S\big(\alpha(\tau), \beta(\tau)\big) = \textstyle\sum_{t=1}^{T}[\rho_\tau(y_t - \alpha(\tau) - \beta(\tau)x_t)] \tag{11}$$

This minimization problem can be solved very efficiently by linear programming methods. For interior solutions, under some regularity conditions, the quantile-based estimator of the parameter vector $[\hat{\alpha}\ (\tau), \hat{\beta}\ (\tau)]$ is asymptotically normal. However, direct estimation of the asymptotic variance-covariance matrix is not always satisfactory. Inference for quantile regression parameters can be made with the bootstrap method.[8] One important property of quantile regression is that the estimators are minimally affected by outliers. Finally, the following relation between the OLS parameters and quantile parameters can be established:

$$\alpha = \int_0^1 \alpha(\tau)d\tau\ \ \&\ \ \beta = \int_0^1 \beta(\tau)d\tau \tag{12}$$

where α and β are from the equation (3).

Since the MV hedge ratio H_{MV} is equal to β, we can now discuss the effectiveness of the *MV* hedge ratio at different quantiles of the spot return. Suppose that $\beta(\tau)$ at 10% and 90% quantiles are 0.75 and 1.25 respectively and the *MV* hedge ratio is 1.0, i.e., β(0.1) = 0.75, β(0.9) = 1.25 and $H_{MV} = \beta = 1.0$. Furthermore, suppose that the hedgers use the *MV* hedge ratio of 1.0. If the spot return is realized at the lower 10% quantile of the spot return, the *MV* hedge ratio leads to over-hedging. Similarly, if the spot return is realized at the top 10% quantile, then the *MV* hedge ratio will lead to under-hedging. If the quantile hedge ratio is the same for all quantiles, then it will also be equal to the conventional *MV* hedge ratio H_{MV} . In this case, the hedger does not have to worry about being asymmetrically affected by changes in the spot prices.

HEDGING EFFECTIVENESS

Finally, the hedge ratios indicate the optimal positions we need to take in the hedging instrument in order to reduce the spot price risk. However, we also need to know how effective such instruments will be in reducing the spot price risk. In this study, we use the hedging effectiveness proposed

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[7] If we only concentrate on the hedging performance at τ quantile and ignore the other quantiles, the hedge ratio should be $\beta(\tau)$.

[8] In this study the quantile regression is implemented using 'quantreg package' in *R* developed by Koenker.

by Shrestha et al. (2018) to compare the effectiveness of ETFs in reducing the spot price risk compared to the traditional futures contracts. We briefly describe the hedging effectiveness in this subsection.

How we measure the hedging effectiveness depends on the objective function considered in the derivation of the optimal hedge ratio. Early studies in hedging (e.g., Johnson, 1960; Ederington and Salas, 2008) derive the so- called minimum variance hedge ratio by minimizing the variance of the hedge portfolio (see equation (2)). Therefore, in the context of variance minimizing hedge ratio, the hedging effectiveness is defined as follows (Johnson, 1960; Ederington and Salas, 2008; Chen et al., 2003; Conlon and Cotter, 2013):

$$HE_{mv} = 1 - \frac{Var(R_H)}{Var(R_S)} \tag{13}$$

where $Var(R_H)$ is the variance of return on the hedged portfolio and $Var(R_S)$ is the variance of the return on the spot position where $R_S = \Delta s_t$. It can be shown that the hedging effectiveness defined above is equal to the R^2 of regression equation (3) used in the estimation of minimum variance hedge ratio (Johnson, 1960). Therefore, a higher value of R^2 represents a better hedging effectiveness.

Similar argument can be followed in defining the hedging effectiveness in the case of quantile hedge ratio. The quantile hedge ratio is obtained by minimizing the sample loss function $L_S\big(\alpha(\tau), \beta(\tau)\big)$ with respect to $\alpha(\tau)$ and $\beta(\tau)$ for a given quantile τ. Therefore, in the context of quantile hedge ratio, we can define the hedging effectiveness for quantile hedge ratio as follows:

$$HE(\tau) = 1 - \frac{V_{unrest}(\tau)}{V_{rest}(\tau)} \tag{14}$$

where,

$$V_{rest}(\tau) = L_S\big(\alpha(\tau), \beta(\tau)\big)\Big|_{\ \alpha(\tau)=0, \beta(\tau)=0} \tag{15}$$

and,

$$V_{unrest}(\tau) = \min_{\alpha(\tau)\beta(\tau)} L_S\big(\alpha(\tau), \beta(\tau)\big) \tag{16}$$

Note that $V_{rest}(\tau)$ is the (restricted) minimum value of the sample loss function when the portfolio does not contain any position in futures contract ($\beta(\tau) = 0$ and $\alpha(\tau) = 0$) and $V_{unrest}(\tau)$ is the (unrestricted) minimum value of the sample loss function where the futures position is selected optimally for a given quantile τ. As mentioned by Koenker and Machado (1999), above definition of hedging effectiveness, in the case of quantile regression, is the natural analog of R^2 in linear regression. Therefore, higher value of $HE(\tau)$ represents a more effective quantile hedge ratio for a given quantile. In this study, we use this measure to analyze the hedging effectiveness for different hedging horizons and quantiles.

EMPIRICAL RESULTS

In this study, we use daily data covering the period from January 4, 2010, to December 29, 2017, with total number of 2,023 observations.[9] The data set includes the daily WTI crude oil spot and near month

[9] Our sample starts after the global financial crisis (GCF) period to exclude the impact of such an unusual event. We would like to thank the reviewer for suggesting dropping the GCF period.

crude oil futures prices. The data set also includes prices of three crude oil future-based ETFs. To date, there are twenty-four listed crude oil ETFs. However, we focus on oil ETFs that replicate the WTI spot Cushing through the nearby month futures contracts and include three ETFs. The three ETFs are the United States Oil Fund (USO), iPath S&P GSCI Crude Oil Total Return (OIL), and United States Short Oil Fund (USL). These oil ETFs have been introduced between the period of 2006-2007 and have preserved a comparatively healthy asset under management and trading volume growth throughout the years. Figure 1 plots the daily crude oil spot and futures as well as the three ETF prices. Table 1 presents detailed information on the three oil ETFs including their ticker codes, inception dates, asset under management and trading volumes.

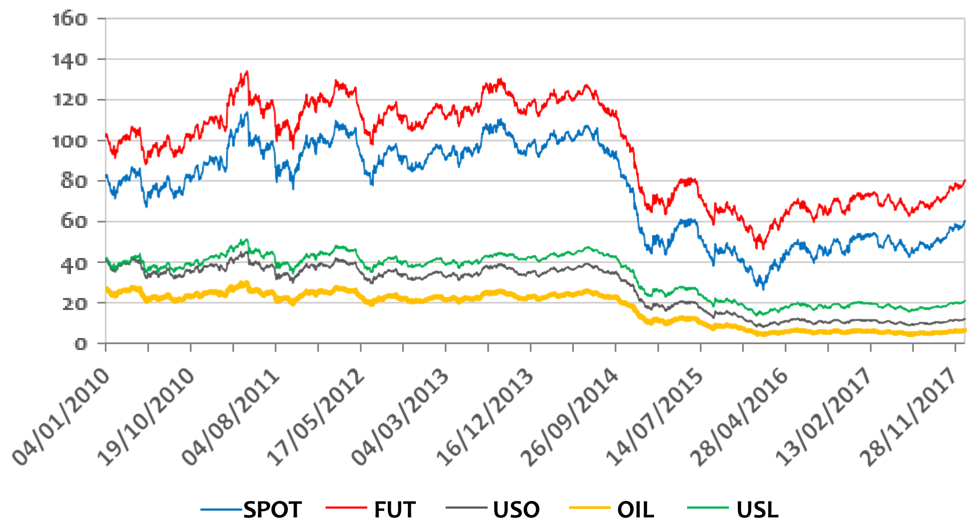

Figure 1. Daily Crude Oil Spot, Futures and Three ETFs Prices from January 4, 2010, to December 2017 Where Futures Price is Shifted Up by Adding $20 to the Futures Price.

Table 1. Information of ETFs

This table presents the ticker codes, inception dates, assets under management and trading volumes for three ETFs used in the study.

Ticker Code	Oil ETFs	Inception Date	Asset Under Management (in USD million)	Trading Volume
U:USO	*United States Oil Fund*	*10-04-2006*	*2,510.00*	*16,012,332*
U:OIL	*iPath S&P GSCI Crude Oil Total Return ETN*	*16-08-2006*	*628.87*	*4,107,677*
U:USL	*United States 12 Month Oil Fund Limited Partnership*	*06-12-2007*	*104.84*	*26,720*

The quantile and *MV* hedge ratios estimated using all three methods (OLS, ECM-OLS and ECM-DOLS) methods and daily data are presented in Table 2. We consider 19 quantiles, $q_i = i \times 0.05, i = 1, 2, \ldots, 19$. These hedge ratios are also plotted in Figures 2, 3 and 4 using OLS, ECM-OLS and ECM-DOLS methods respectively. The quantile hedge ratios are found to be the lowest for OIL, followed by Futures, USO and USL. For USL, the quantile hedge ratios are significantly higher than the naive hedge ratio of 1.0.[10] The maximum absolute difference between the OLS based quantile hedge ratios and ECM-OLS based quantile hedge ratios is approximately 0.0497. Similarly, the maximum absolute difference between the ECM-OLS based quantile hedge ratio and ECM-DOLS based quantile hedge ratio is approximately 0.0003.

[10] For example, based on ECM-OLS methods, the maximum difference between the quantile hedge ratios and naive hedge ratio is 16.10% (for 95th percentile) . Similarly, the minimum difference between the quantile hedge ratios and naive hedge ratio is 14.328% (for 5th percentile). Even the MV hedge ratio is 15.68% higher than the naive hedge ratio.

Table 2. Hedge Ratio Using OLS, ECM-OLS and ECM-DOLS Methods (Daily Data)
This table presents the hedge ratios with Futures and three ETFs as hedging instruments across various quantiles using daily data. Panel A presents the *MV* and quantile hedge ratios obtained using the OLS Method. The *MV* hedge ratios are shown at the last row. Similarly, Panel B presents the *MV* and quantile hedge ratios obtained using the ECM-OLS method. Finally, Panel C presents the *MV* and quantile hedge ratios obtained using the ECM-DOLS method.

	Panel A:	OLS Method			Panel B:	ECM-OLS Method			Panel C:	ECM-DOLS Method		
Commodity	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**
0.05	*0.9507*	*1.0114*	*0.9596*	*1.1267*	*0.9498*	*1.0282*	*0.9112*	*1.1433*	*0.9496*	*1.0271*	*0.9121*	*1.1425*
0.10	*0.9997*	*1.0222*	*0.9526*	*1.1319*	*0.9895*	*1.0283*	*0.9253*	*1.1467*	*0.9888*	*1.0261*	*0.9259*	*1.1489*
0.15	*1.0000*	*1.0193*	*0.9385*	*1.1391*	*0.9963*	*1.0192*	*0.9248*	*1.1596*	*0.9963*	*1.0191*	*0.9240*	*1.1598*
0.20	*1.0000*	*1.0161*	*0.9324*	*1.1465*	*0.9993*	*1.0123*	*0.9278*	*1.1499*	*0.9993*	*1.0122*	*0.9274*	*1.1490*
0.25	*1.0000*	*1.0153*	*0.9303*	*1.1474*	*0.9999*	*1.0129*	*0.9326*	*1.1532*	*0.9999*	*1.0130*	*0.9326*	*1.1520*
0.30	*1.0000*	*1.0165*	*0.9263*	*1.1525*	*0.9998*	*1.0098*	*0.9222*	*1.1560*	*0.9999*	*1.0098*	*0.9221*	*1.1559*
0.35	*1.0000*	*1.0112*	*0.9239*	*1.1562*	*0.9999*	*1.0087*	*0.9192*	*1.1509*	*0.9999*	*1.0086*	*0.9193*	*1.1510*
0.40	*1.0000*	*1.0091*	*0.9181*	*1.1607*	*0.9998*	*1.0091*	*0.9195*	*1.1444*	*0.9998*	*1.0091*	*0.9195*	*1.1443*
0.45	*1.0000*	*1.0125*	*0.9192*	*1.1507*	*0.9997*	*1.0126*	*0.9173*	*1.1508*	*0.9997*	*1.0126*	*0.9173*	*1.1509*
0.50	*1.0000*	*1.0115*	*0.9228*	*1.1517*	*0.9998*	*1.0125*	*0.9203*	*1.1453*	*0.9997*	*1.0124*	*0.9203*	*1.1451*
0.55	*1.0000*	*1.0081*	*0.9181*	*1.1538*	*0.9995*	*1.0089*	*0.9223*	*1.1533*	*0.9996*	*1.0095*	*0.9220*	*1.1534*
0.60	*1.0000*	*1.0120*	*0.9127*	*1.1546*	*0.9994*	*1.0069*	*0.9188*	*1.1569*	*0.9997*	*1.0066*	*0.9189*	*1.1570*
0.65	*1.0000*	*1.0066*	*0.9088*	*1.1614*	*0.9997*	*1.0053*	*0.9235*	*1.1536*	*0.9998*	*1.0047*	*0.9234*	*1.1528*
0.70	*1.0000*	*1.0054*	*0.9085*	*1.1635*	*0.9999*	*1.0051*	*0.9170*	*1.1592*	*0.9999*	*1.0049*	*0.9169*	*1.1582*
0.75	*1.0000*	*1.0069*	*0.9138*	*1.1561*	*0.9998*	*1.0097*	*0.9128*	*1.1561*	*1.0000*	*1.0108*	*0.9131*	*1.1561*
0.80	*1.0000*	*1.0152*	*0.9108*	*1.1615*	*0.9998*	*1.0116*	*0.9090*	*1.1520*	*1.0001*	*1.0113*	*0.9090*	*1.1523*
0.85	*1.0000*	*1.0238*	*0.9130*	*1.1610*	*1.0003*	*1.0079*	*0.8986*	*1.1512*	*1.0003*	*1.0069*	*0.8988*	*1.1517*
0.90	*1.0024*	*1.0239*	*0.9079*	*1.1753*	*1.0006*	*1.0140*	*0.8959*	*1.1433*	*1.0008*	*1.0140*	*0.8961*	*1.1433*
0.95	*1.0138*	*1.0333*	*0.9302*	*1.1196*	*1.0001*	*1.0355*	*0.8805*	*1.1610*	*1.0003*	*1.0341*	*0.8806*	*1.1580*
MVHR	*0.9608*	*1.0109*	*0.8829*	*1.1508*	*0.9685*	*1.0151*	*0.8981*	*1.1568*	*0.9685*	*1.0151*	*0.8981*	*1.1568*

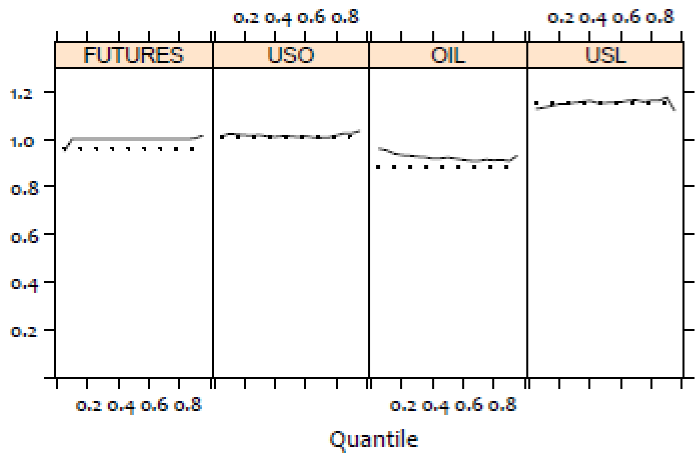

Figure 2. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using daily data and OLS method. The hedge ratios are presented in Panel A, Table 2. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

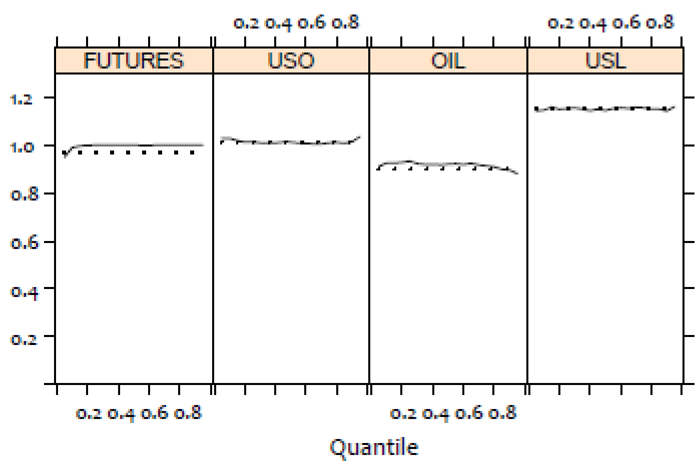

Figure 3. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using daily data and ECM-OLS method. The hedge ratios are presented in Panel B, Table 2. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

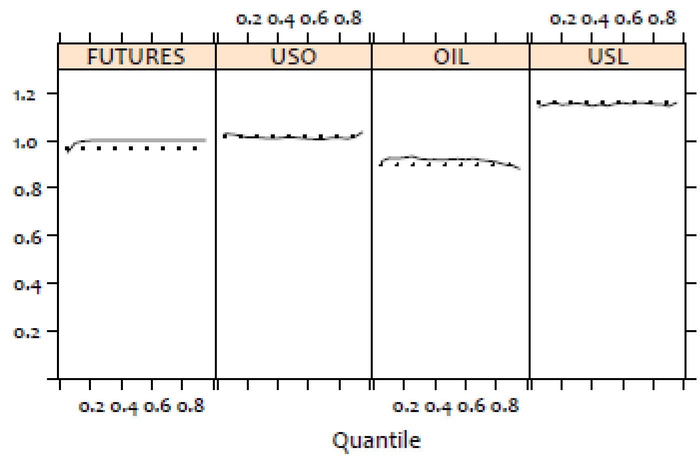

Figure 4. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using daily data and ECM-DOLS method. The hedge ratios are presented in Panel C, Table 2. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

In order to evaluate the impact of increase in hedging horizon, we also estimate the quantile and *MV* hedge ratios using all three methods using weekly and 4-weekly data. The results for the weekly data are presented in Table 3 and plotted in Figures 5, 6 and 7. The maximum absolute difference between the OLS based quantile hedge ratio and ECM-OLS based quantile hedge ratio is approximately 0.0850. Similarly, the maximum absolute difference between the ECM-OLS based quantile hedge ratio and ECM-DOLS based quantile hedge ratio is approximately 0.0093. Finally, the results for the 4-weekly data are presented in Table 4 and plotted in Figures 8, 9 and 10.The maximum absolute difference between the OLS based quantile hedge ratio and ECM-OLS based quantile hedge ratio is approximately 0.0649. Similarly, the maximum absolute difference between the ECM-OLS based quantile hedge ratio and ECM-DOLS based quantile hedge ratio is approximately 0.0426. Consistent with the daily data, the quantile hedge ratios are found to be the lowest for OIL, followed by Futures, USO and USL for the weekly and 4-weekly data.

Table 3. Hedge Ratio Using OLS, ECM-OLS and ECM-DOLS Methods (Weekly Data)

This table presents the hedge ratios with Futures and three ETFs as hedging instruments across various quantiles using weekly data. Panel A presents the *MV* and quantile hedge ratios obtained using the OLS Method. The *MV* hedge ratios are shown at the last row. Similarly, Panel B presents the *MV* and quantile hedge ratios obtained using the ECM-OLS method. Finally, Panel C presents the *MV* and quantile hedge ratios obtained using the ECM-DOLS method.

	Panel A:	**OLS Method**			**Panel B:**	**ECM-OLS Method**			**Panel C:**	**ECM-DOLS Method**		
Commodity	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**
0.05	*0.9514*	*1.0519*	*0.9369*	*1.1589*	*1.0101*	*1.0565*	*0.9243*	*1.1223*	*1.0101*	*1.0562*	*0.9248*	*1.1232*
0.10	*0.9947*	*1.0277*	*0.9376*	*1.1303*	*1.0020*	*1.0510*	*0.9350*	*1.1427*	*1.0020*	*1.0511*	*0.9350*	*1.1394*
0.15	*1.0000*	*1.0110*	*0.9217*	*1.1461*	*1.0002*	*1.0362*	*0.9298*	*1.1357*	*1.0002*	*1.0362*	*0.9291*	*1.1341*
0.20	*1.0000*	*1.0173*	*0.9167*	*1.1503*	*1.0012*	*1.0305*	*0.9302*	*1.1458*	*1.0012*	*1.0305*	*0.9299*	*1.1438*
0.25	*1.0000*	*1.0170*	*0.9155*	*1.1447*	*1.0015*	*1.0360*	*0.9388*	*1.1395*	*1.0015*	*1.0363*	*0.9391*	*1.1380*
0.30	*1.0000*	*1.0116*	*0.9216*	*1.1502*	*1.0012*	*1.0324*	*0.9346*	*1.1569*	*1.0012*	*1.0331*	*0.9341*	*1.1553*
0.35	*1.0000*	*1.0175*	*0.9187*	*1.1486*	*1.0014*	*1.0310*	*0.9248*	*1.1479*	*1.0014*	*1.0313*	*0.9251*	*1.1470*
0.40	*1.0000*	*1.0130*	*0.9170*	*1.1295*	*1.0016*	*1.0278*	*0.9290*	*1.1502*	*1.0016*	*1.0275*	*0.9283*	*1.1506*
0.45	*1.0000*	*1.0083*	*0.9192*	*1.1327*	*1.0012*	*1.0207*	*0.9240*	*1.1448*	*1.0012*	*1.0206*	*0.9257*	*1.1437*
0.50	*1.0000*	*1.0065*	*0.9232*	*1.1505*	*1.0012*	*1.0199*	*0.9323*	*1.1595*	*1.0012*	*1.0196*	*0.9299*	*1.1588*
0.55	*1.0000*	*1.0112*	*0.9133*	*1.1417*	*1.0012*	*1.0159*	*0.9286*	*1.1570*	*1.0012*	*1.0154*	*0.9267*	*1.1583*
0.60	*1.0000*	*1.0075*	*0.9108*	*1.1404*	*1.0011*	*1.0178*	*0.9262*	*1.1516*	*1.0011*	*1.0195*	*0.9257*	*1.1534*
0.65	*1.0000*	*1.0049*	*0.9055*	*1.1399*	*1.0017*	*1.0154*	*0.9224*	*1.1518*	*1.0017*	*1.0155*	*0.9241*	*1.1528*
0.70	*1.0000*	*0.9989*	*0.9024*	*1.1378*	*1.0016*	*1.0167*	*0.9212*	*1.1517*	*1.0016*	*1.0181*	*0.9236*	*1.1532*
0.75	*1.0000*	*1.0041*	*0.8971*	*1.1364*	*1.0016*	*1.0169*	*0.9129*	*1.1482*	*1.0016*	*1.0180*	*0.9114*	*1.1499*
0.80	*1.0000*	*1.0178*	*0.9025*	*1.1310*	*1.0020*	*1.0130*	*0.8955*	*1.1417*	*1.0020*	*1.0223*	*0.8985*	*1.1397*
0.85	*1.0004*	*1.0201*	*0.9080*	*1.1222*	*1.0023*	*1.0255*	*0.9002*	*1.1569*	*1.0023*	*1.0244*	*0.9021*	*1.1560*
0.90	*1.0208*	*1.0116*	*0.9090*	*1.1189*	*1.0025*	*1.0206*	*0.8938*	*1.1444*	*1.0025*	*1.0246*	*0.8952*	*1.1497*
0.95	*1.0205*	*1.0746*	*0.9203*	*1.1137*	*1.0045*	*1.0629*	*0.8354*	*1.1053*	*1.0045*	*1.0595*	*0.8333*	*1.1050*
MVHR	*0.9922*	*1.0268*	*0.8902*	*1.1425*	*1.0029*	*1.0349*	*0.9082*	*1.1555*	*1.0029*	*1.0350*	*0.9086*	*1.1555*

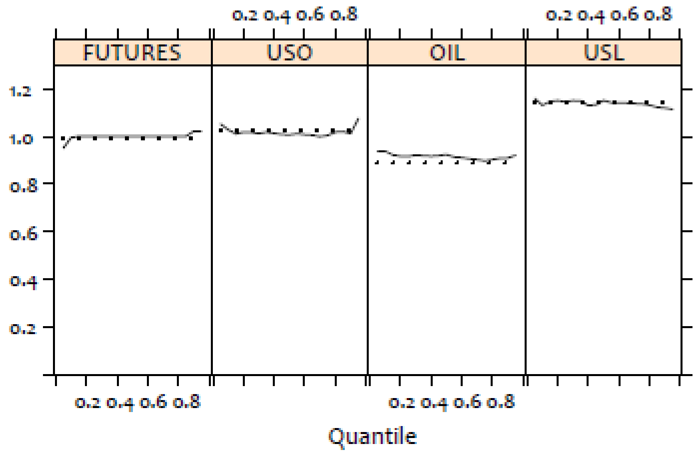

Figure 5. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using weekly data and OLS method. The hedge ratios are presented in Panel A, Table 3. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

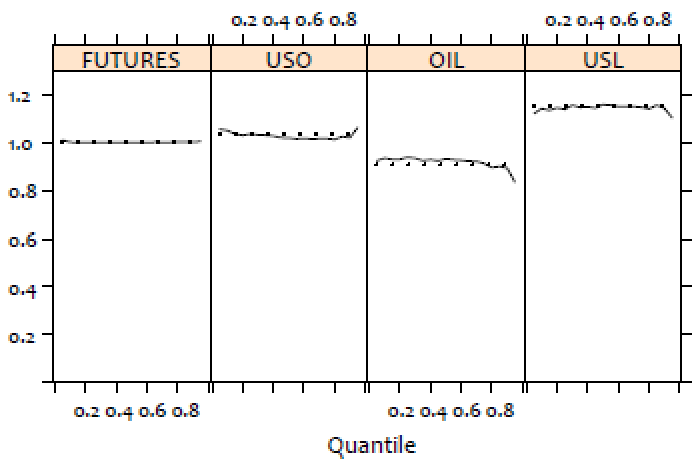

Figure 6. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using weekly data and ECM-OLS method. The hedge ratios are presented in Panel B, Table 3. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

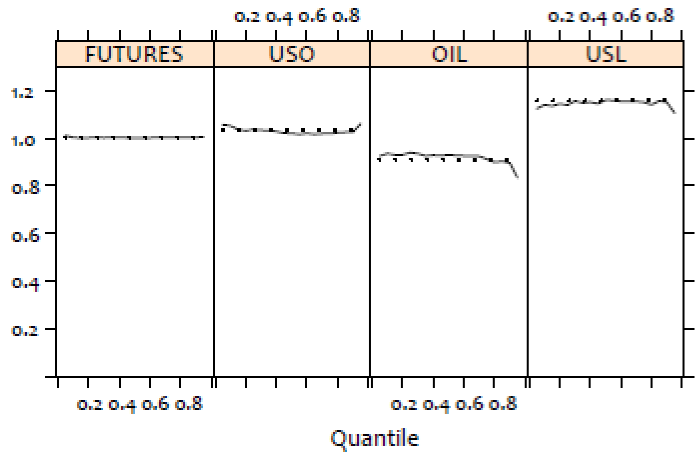

Figure 7. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using weekly data and ECM-DOLS method. The hedge ratios are presented in Panel C, Table 3. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

Table 4. Hedge Ratio Using OLS, ECM-OLS and ECM-DOLS Methods (4-Weekly Data)

This table presents the hedge ratios with Futures and three ETFs as hedging instruments across various quantiles using 4-weekly data. Panel A presents the *MV* and quantile hedge ratios obtained using the OLS Method. The *MV* hedge ratios are shown at the last row. Similarly, Panel B presents the *MV* and quantile hedge ratios obtained using the ECM-OLS method. Finally, Panel C presents the *MV* and quantile hedge ratios obtained using the ECM-DOLS method.

	Panel A:	OLS Method			Panel B:	ECM-OLS Method			Panel C:	ECM-DOLS Method		
Commodity	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**
0.05	1.0258	1.0643	0.9447	1.1084	1.0199	1.0691	0.9791	1.1365	1.0199	1.0682	0.9819	1.1289
0.10	1.0077	1.0760	0.9308	1.1385	1.0092	1.0336	0.9435	1.1439	1.0092	1.0217	0.9412	1.1549
0.15	1.0037	1.0448	0.9194	1.1893	1.0047	1.0343	0.9265	1.1675	1.0047	1.0095	0.9324	1.1647
0.20	1.0000	1.0270	0.9140	1.2028	1.0044	1.0333	0.9257	1.1649	1.0044	1.0156	0.9294	1.2075
0.25	1.0000	1.0317	0.9268	1.2029	1.0024	1.0288	0.9147	1.1691	1.0024	0.9916	0.9145	1.1637
0.30	1.0000	1.0228	0.9209	1.2164	1.0020	1.0117	0.9158	1.2082	1.0020	0.9907	0.9192	1.2184
0.35	1.0000	1.0246	0.9249	1.2008	1.0014	1.0014	0.9195	1.2061	1.0014	1.0080	0.9212	1.2140
0.40	1.0000	1.0219	0.9347	1.1922	1.0013	1.0039	0.9170	1.2132	1.0013	1.0109	0.9271	1.2173
0.45	1.0000	1.0297	0.9355	1.2141	1.0014	1.0123	0.9195	1.2098	1.0014	1.0113	0.9284	1.2174
0.50	1.0000	1.0245	0.9393	1.2031	1.0016	1.0180	0.9312	1.1985	1.0016	1.0163	0.9270	1.2027
0.55	1.0000	1.0159	0.9273	1.2109	1.0015	1.0114	0.9240	1.2018	1.0015	1.0090	0.9251	1.2008
0.60	1.0000	1.0151	0.9296	1.2031	1.0014	1.0103	0.9198	1.1908	1.0014	1.0150	0.9126	1.2049
0.65	1.0000	1.0100	0.9268	1.2019	1.0006	1.0131	0.9187	1.1865	1.0006	1.0134	0.9022	1.2067
0.70	1.0000	0.9900	0.9161	1.2156	1.0007	1.0047	0.8906	1.2143	1.0007	1.0145	0.8876	1.2125
0.75	1.0000	1.0013	0.9002	1.2154	1.0000	1.0121	0.8848	1.2245	1.0000	1.0084	0.8815	1.2050
0.80	1.0000	1.0024	0.9012	1.1859	1.0001	0.9925	0.8823	1.2099	1.0001	1.0076	0.8789	1.1980
0.85	1.0000	0.9965	0.8961	1.2541	1.0017	0.9934	0.8673	1.2215	1.0017	1.0138	0.8837	1.2019
0.90	1.0047	1.0166	0.8706	1.2561	1.0021	1.0041	0.8906	1.1912	1.0021	1.0227	0.8947	1.2025
0.95	1.0337	0.9691	0.8614	1.1877	1.0049	1.0225	0.8906	1.2323	1.0049	1.0499	0.9056	1.1979
MVHR	1.0075	1.0129	0.9070	1.2049	1.0046	1.0052	0.9048	1.2150	1.0046	1.0093	0.9063	1.2149

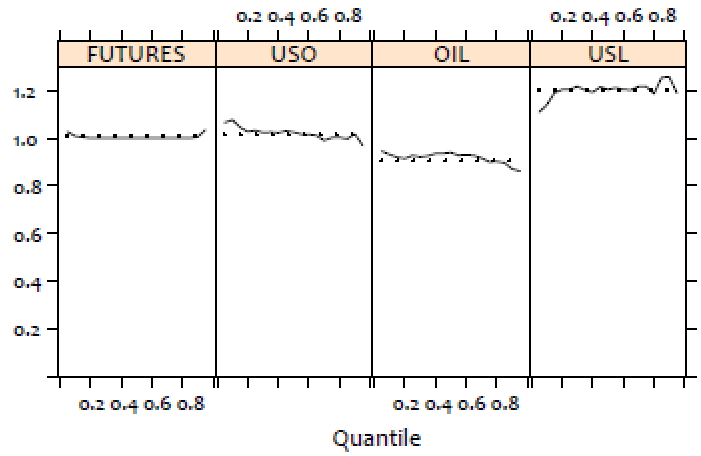

Figure 8. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using 4-weekly data and OLS method. The hedge ratios are presented in Panel A, Table 4. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

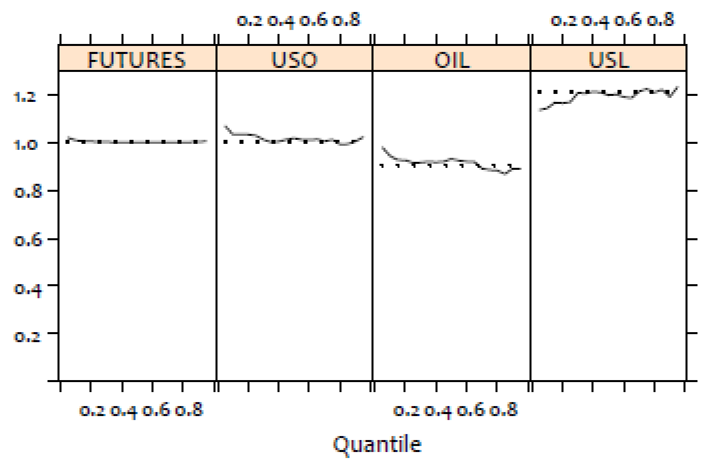

Figure 9. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using 4-weekly data and ECM-OLS method. The hedge ratios are presented in Panel B, Table 4. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

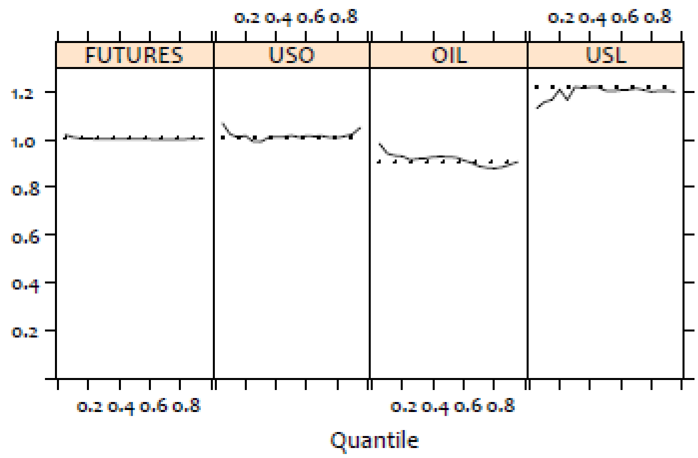

Figure 10. This figure plots the minimum variance (dotted line) and quantile hedge ratios for the four hedging instruments estimated using 4-weekly data and ECM-DOLS method. The hedge ratios are presented in Panel C, Table 4. The vertical axis represents the hedge ratio and the horizontal axis represents the quantiles. Since the minimum variance hedge ratio (MVHR) does not depend on quantiles, it is represented by a horizontal (dotted) line.

The main reason we want to use quantile hedge ratios has to do with the possibility that the quantile hedge ratios are significantly different from the *MV* hedge ratio. If we use the *MV* hedge ratio, we implicitly assume that the quantile hedge ratios are the same for all quantiles. Therefore, we would be interested to know how close the quantile hedge ratios are to the *MV* hedge ratio. This closeness can be measured using the following distance (D) measure:

$$D = \frac{1}{19}\sum_{i=1}^{19}|QH_i - MV| \tag{17}$$

where $QH_i, i = 1, 2, \ldots, 19$, denotes the quantile hedge ratio for quantile i. The minimum value D would take is zero, in which case the quantile hedge ratios are constant and are equal to the *MV* hedge ratio. The distance measures for the daily data are presented in the first row of Table 5. The maximum value of the distance measure is 0.0300 for the futures contract based on the ECM- OLS based hedge ratios.[11] Similarly, the distance measure for the weekly and 4-weekly data are presented in second and third rows respectively in Table 5. When we increase the hedging horizon, the distance measure (D) seems to decrease for the futures. However, the distance measures for the three ETFs increase with the increase in the hedging horizon in general.

[11] As stated later on, the hedging effectiveness of the ECM-OLS is higher than that of the OLS method. Furthermore, the hedging effectiveness of the ECM-OLS method is close to the effectiveness of the ECM-DOLS method. Therefore, we will concentrate on the ECM-OLS method when interpreting the empirical results.

Table 5. Distance of Quantile Hedge Ratios from *MV* Hedge Ratio

This table presents the distances (D) of quantile hedge ratios from *MV* hedge ratio, where D is defined as $D = \frac{1}{19}\sum_{i=1}^{19}|QH_i - MV|$ where QH_i is quantile hedge ratio for the i^{th} quantile. The distances for all three methods (OLS, EMC-OLS and ECM- DOLS) as well as all three hedging horizons (daily, weekly and 4-weekly) are presented.

	Panel A:	**OLS Method**			**Panel B:**	**ECM-OLS Method**			**Panel C:**	**ECM-DOLS Method**		
Data Frequency	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**	**Futures**	**USO**	**OIL**	**USL**
daily	*0.0385*	*0.0058*	*0.0406*	*0.0101*	*0.0300*	*0.0068*	*0.0197*	*0.0059*	*0.0300*	*0.0066*	*0.0197*	*0.0057*
weekly	*0.0114*	*0.0171*	*0.0254*	*0.0099*	*0.0017*	*0.0133*	*0.0210*	*0.0114*	*0.0017*	*0.0123*	*0.0205*	*0.0113*
4-weekly	*0.0083*	*0.0187*	*0.0210*	*0.0206*	*0.0035*	*0.0144*	*0.0218*	*0.0243*	*0.0035*	*0.0106*	*0.0208*	*0.0200*

In order to analyze how effective the ETFs can be as hedging instruments; we compute the hedging effectiveness for the futures and three ETFs. In general, we find the hedging effectiveness of hedge ratios calculated using the ECM-OLS method to be higher than that of hedge ratios calculated using the OLS method. Furthermore, the hedging effectiveness based on the ECM- OLS method are found to be very close to the hedging effectiveness based on the ECM-DOLS method. Therefore, we only present the hedging effectiveness of the ECM-OLS based hedge ratios in Table 6 for daily, weekly and 4-weekly data.

The hedging effectiveness of hedge ratios based on the futures contract is the highest, followed by USO, OIL and USL ETFs. The average effectiveness over all quantiles improves for all instruments (e.g., futures and three ETFs) as we increase the hedging horizon from 1-day to 4-week. Furthermore, the hedging effectiveness of three ETFs compared to the futures contract improves with the hedging horizon. For example, the hedging effectiveness of the futures is 12.70% higher compared to the hedging effectiveness of USO for 1-day hedging horizon. However, the hedging effectiveness of the futures is only 6.36% higher compared to USO for 4-week hedging horizon. It is also interesting to note that the hedge ratios based on futures perform the best, followed by USO, OIL and USL respectively.[12] The performance is highest for the middle quantiles compared to extreme quantile in pairwise comparison as shown in Figures 11 (daily), 12 (weekly) and 13 (4-weekly).[13]

[12] When it comes to the hedging effectiveness of the ETFs, is seems to be positively related to the asset under management and trading volume. We would like to thank the reviewer for pointing this out.

[12] One of the objectives of the study is to analyze the impact of changes on the investment horizon. We find the investment horizon has impacts on the hedge ratio as well as the hedging effectiveness. There can be two reasons for the effects. Firstly, shorter horizons like 1-day are dominated by short-term relations between the spot price and the prices of hedging instruments. Similarly, longer horizons like four weeks are dominated by long-term relations. The long-term and short-term relations could be different. Secondly, higher frequency data like daily data may contain noise that could be averaged out over a more extended period.

Table 6. Hedging Effectiveness of Quantile Hedge Ratios

This table presents the hedging effectiveness of quantile hedge ratios estimated using daily, weekly and 4-weekly data. Since the ECM-OLS model performs better than OLS method and performance of ECM-OLS method is very close to that of ECM-DOLS, only the hedging effectiveness of ECM-OLS is presented.

Commodity	**Quantiles**																		
	0.05	*0.1*	*0.15*	*0.2*	*0.25*	*0.3*	*0.35*	*0.4*	*0.45*	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
	Daily Data																		
Futures	0.91	0.89	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.89	0.89	0.89	0.90	0.90	0.91	0.92	0.93
USO	0.90	0.86	0.83	0.80	0.78	0.76	0.75	0.74	0.73	0.72	0.72	0.72	0.73	0.74	0.75	0.77	0.80	0.84	0.89
OIL	0.89	0.84	0.80	0.77	0.74	0.72	0.71	0.69	0.68	0.68	0.68	0.68	0.69	0.70	0.71	0.73	0.76	0.80	0.87
USL	0.88	0.82	0.77	0.74	0.71	0.68	0.66	0.65	0.64	0.64	0.64	0.64	0.65	0.66	0.68	0.71	0.75	0.80	0.87
	Weekly Data																		
Futures	0.96	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.96	0.96	0.97
USO	0.96	0.94	0.91	0.89	0.88	0.87	0.86	0.85	0.84	0.84	0.84	0.84	0.84	0.85	0.86	0.87	0.89	0.91	0.95
OIL	0.94	0.90	0.87	0.85	0.83	0.82	0.81	0.80	0.79	0.79	0.78	0.78	0.79	0.79	0.80	0.82	0.84	0.88	0.92
USL	0.92	0.87	0.83	0.80	0.78	0.76	0.74	0.73	0.73	0.72	0.72	0.73	0.73	0.75	0.76	0.79	0.81	0.85	0.91
	4-Weekly Data																		
Futures	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.99	0.99
USO	0.97	0.96	0.94	0.93	0.92	0.91	0.90	0.90	0.89	0.89	0.89	0.89	0.90	0.90	0.91	0.92	0.93	0.94	0.97
OIL	0.97	0.95	0.93	0.91	0.90	0.89	0.88	0.87	0.87	0.86	0.86	0.86	0.86	0.87	0.88	0.89	0.90	0.92	0.96
USL	0.94	0.89	0.86	0.84	0.82	0.81	0.80	0.79	0.79	0.79	0.79	0.79	0.79	0.81	0.83	0.85	0.87	0.91	0.95

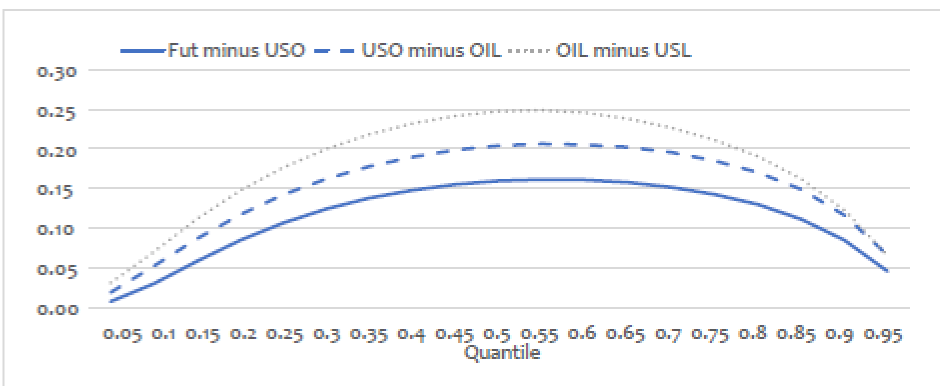

Figure 11. This figure plots the difference in hedging effectiveness between two instruments taken at a time estimated using daily data.

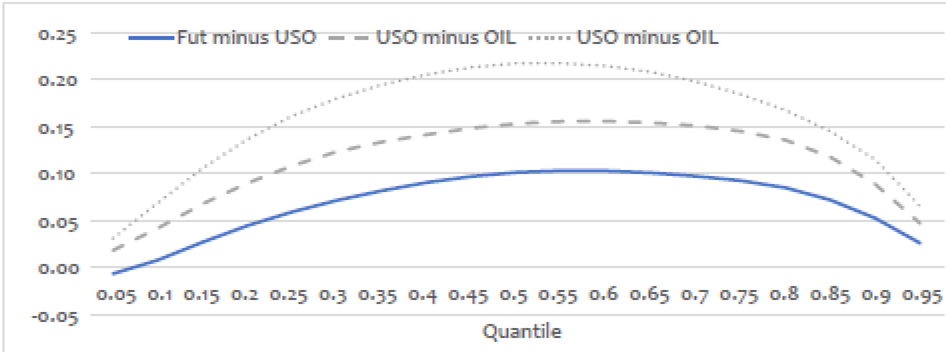

Figure 12. This figure plots the difference in hedging effectiveness between two instruments taken at a time estimated using weekly data.

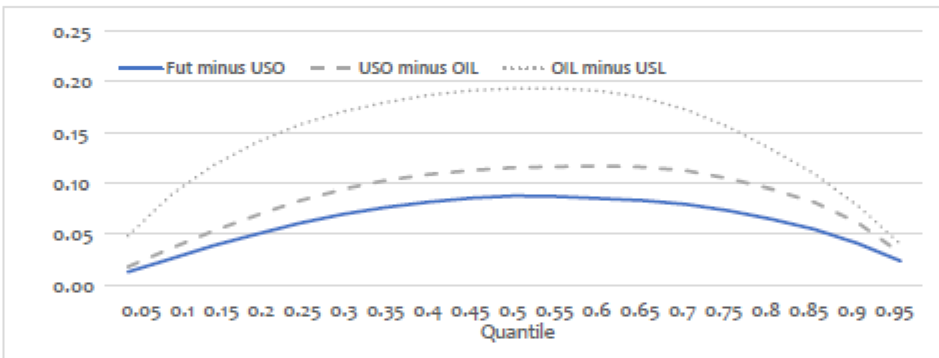

Figure 13. This figure plots the difference in hedging effectiveness between two instruments taken at a time estimated using 4-weekly data.

Finally, we would like to comment on the economic significance of the difference between the hedge ratios. Since USO performs close to futures in terms of effectiveness at the extreme quantiles, it is useful to compare the economic significance of the difference between hedge ratios based on futures and USO. For the daily data, the maximum difference among the quantile hedge ratios for the futures contract is 0.0509 for the ECM-OLS method, which is approximately 5.09% and is considered economically significant. The figures for weekly and 4-weekly data are approximately 1.0% and 2.0%, respectively. In terms of transaction cost, the USO is better because this does not require rollover of the contract. However, when using short-term futures contracts for hedging longer horizons, contract rollover is necessary, which involves extra transaction costs.

CONCLUSION

In this study, we empirically investigate the contributions of crude oil futures contract and three oil ETFs in hedging oil price risk. We use daily data from January 4, 2010, up to December 29, 2017. We estimate the quantile hedge as well as minimum variance hedge ratios using three different methods: (i) OLS, (ii) ECM-OLS and (iii) ECM-DOLS. We also compute the hedging effectiveness of futures and the three oil ETFs. In order to analyze the impact of hedging horizon on the hedge ratio as well as the hedging effectiveness, we use daily, weekly and 4-weekly data.

We have some interesting findings. There are significant differences between the quantile hedge ratios based on OLS and ECM-OLS method. However, the hedge ratios based on ECM-OLS method are closer to the ones based on the ECM-DOLS method. Oil ETF is found to have the lowest hedge ratio, followed by futures, USO, and USL. The quantile hedge ratios for the futures approach the MV hedge ratio with the increase in the hedging horizon. However, the opposite is the behaviour of the hedge ratios based on the three ETFs. In terms of the hedging effectiveness, the futures hedge ratios perform the best, followed by USO, OIL and USL. Interestingly, we find the difference in the pairwise performance to be lowest for the extreme quantiles and highest for the middle quantiles. The hedging effectiveness increases with the increase in the hedging horizon for all instruments. The hedging effectiveness among the ETFs seem to be positively related to the size (asset under management) and trading volume. USO, with the highest size and trading volume, performs close to the futures for the extreme quantiles. However, for the middle quantiles the hedging effectiveness of the USO is significantly lower. Therefore, we conclude that some ETFs can contribute to hedging at least for the extreme quantiles. Since ETFs does not require the rolling of futures contract, they may be used as alternative hedging instruments.

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