Hedging Effectiveness of Energy Exchange Traded Funds

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ABSTRACT

Hedging Effectiveness of Energy Exchange Traded Funds

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This thesis examines the hedging effectiveness of energy Exchange Traded Funds (ETFs). ETFs provide small investors the opportunity to hedge against the risk of price changes in commodities such as crude oil, instead of using commodity futures contracts to hedge, which require a high initial margin. In this thesis, I address the hedging effectiveness of energy ETFs in hedging against fluctuations in the price of crude oil. I apply various models of hedging such as the minimum variance hedge ratio model (MVHR) in which the measure of risk is the variance of the change in the value of the hedged portfolio, and other models in which the measure of risk is the value at risk (VaR), the conditional value at risk (CVaR) and modified value at risk (MVaR) of the hedged portfolio. I investigate the hedging effectiveness of energy ETFs in both in-sample and out-of-sample periods. My results indicate that energy ETFs are effective in reducing the risks associated with fluctuation in the price of crude oil.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

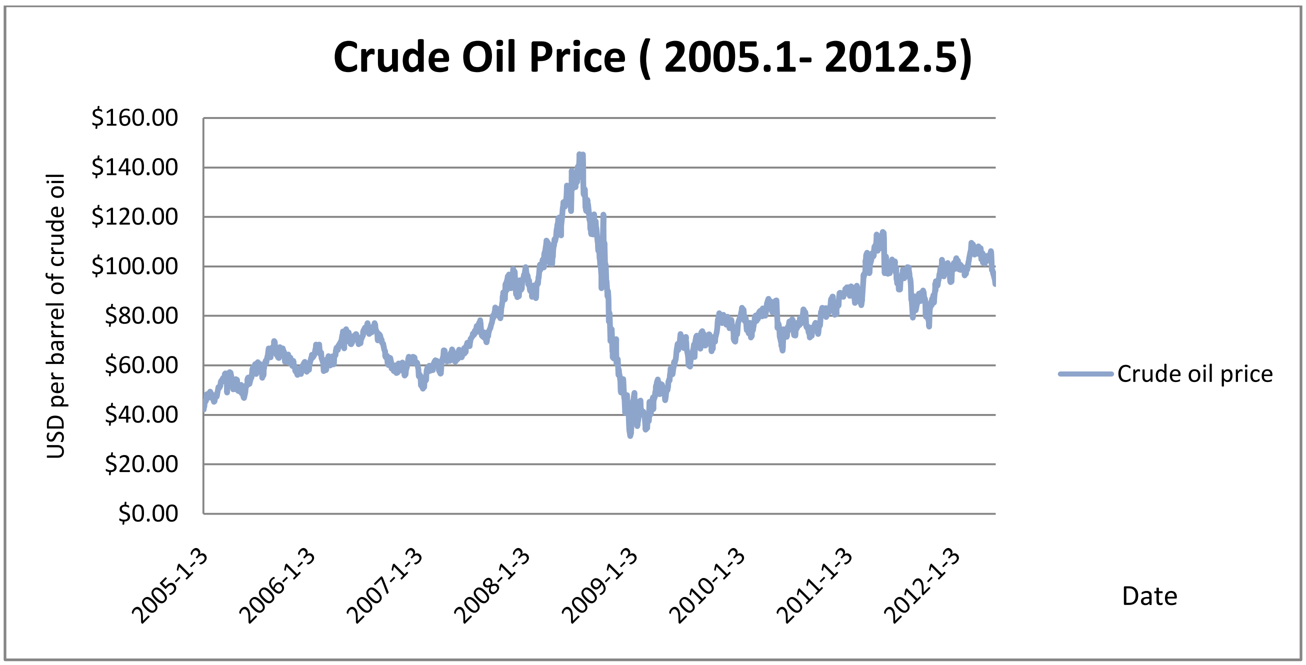
Chapter I. Introduction

Exchange-traded funds (ETF) are new investment vehicles that can be traded on stock exchanges. Since they are traded like stocks, ETFs can be bought or sold at intraday prices not necessarily at end-of-day prices as with mutual funds. According to the descriptions of their investment strategies, ETFs hold a pool of assets such as stocks, bonds and commodities, etc., the return on which is expected to be as close as possible to a specific benchmark, as for example, the S&P 500 stock index.

In comparison to mutual funds, ETFs not only are cost-effective because of lower management fees and brokerage costs but also provide investors with exposure to a broad range of assets such as commodities and emerging market equities, both of which are either prohibitively expensive or inaccessible. Commodity ETFs account for 10% of total ETF assets in 2011 and have become one of the most important tools to obtain exposure to commodity prices (Kosev and Williams, 2011). The advantage offered by commodity ETFs is that investors can obtain exposures to commodity prices without being required to buy and store the physical commodities.

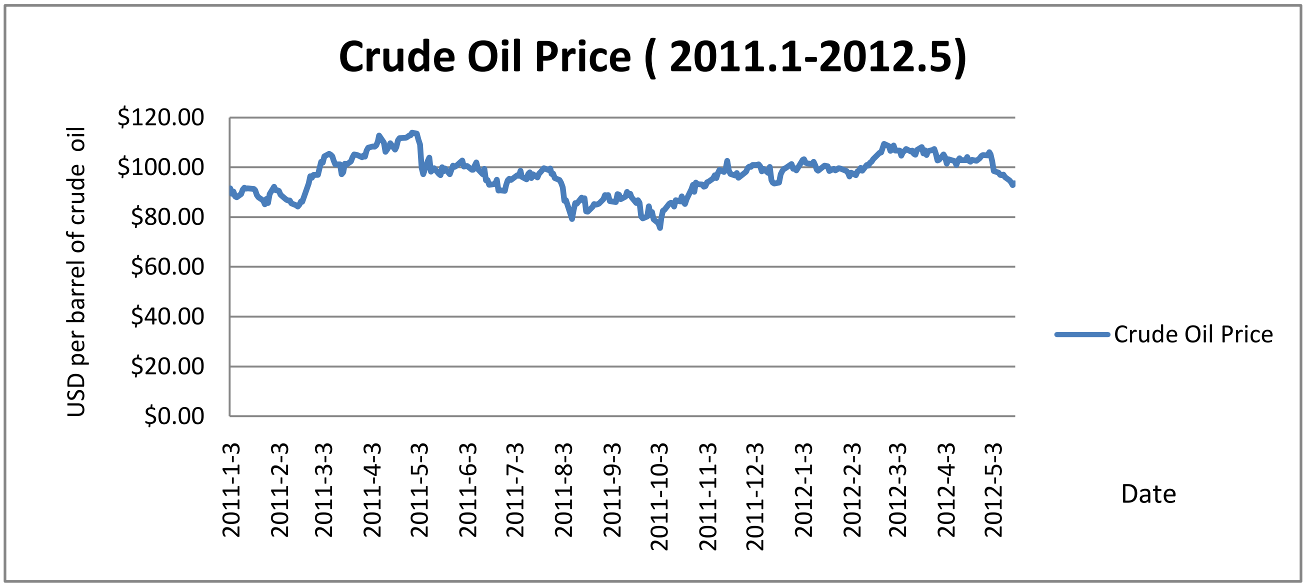
In recent years, crude oil investors or consumers are exposed to the risk on account of the crude oil price fluctuation. Figure 1 shows the price change of crude oil from January 2005 to May 2012. Obviously, the price of crude oil fluctuates over time, which demonstrates the risk faced by crude oil investors or consumers. For example, in 2008, the spot price of crude oil plummeted by nearly 71.4% within six months. If crude oil investors or consumers had not assumed positions to hedge their position, they would have probably incurred huge losses. Figure 2 shows that in the recent period extending, from January 2011 to May 2012, the price of crude oil has been volatile, fluctuating around $ 100 per barrel. Therefore, it is necessary to hedge against crude oil price fluctuation.

Figure 1: Daily price of Crude Oil from January 2005 to May 2012



Source: Bloomberg

Figure 2: Daily price of Crude Oil from January 2011 to May 2012



Source: Bloomberg

Historically, hedging with the use of financial instruments has been restricted to the use of derivatives (i.e., futures, options and forwards contracts) whose pricing mechanics are based on a complex mathematical formula. The Black and Scholes option pricing model, which is generally used by sophisticated investors, involves complexities which may make it difficult for small investors to use in hedging. Moreover, derivatives such as forwards contracts are not accessible to small or individual investors since only large institutions or companies are able to make the agreements with each other. Forwards contracts are traded over the counter and they have to be held to maturity. In addition, high initial margin required by futures contracts and the short time to delivery also limit small investors from using conventional derivatives to hedge. With the advent of ETFs, however, a broad range of investor groups is able to access hedging tools since ETFs are listed and traded as securities on stock exchanges. Commodity ETFs help farmers or producers to hedge the price risk associated with the sale of their products and the buyers to fix the price of their targeted products. Moreover, portfolio managers are able to adjust hedge ratios in a short term such as every week if they use ETFs to hedge.

Recently, hedging against price fluctuation of commodities such as crude oil using commodity ETFs is becoming more and more popular primarily due to the higher liquidity of ETFs compared to futures contracts. Moreover, commodity ETFs allow investors to take positions with lower entrance fees and lower holding or management fees. In addition, commodity ETFs require a much smaller initial investment margin than futures contracts do. For example, one crude oil futures contract on 1000 barrels of oil requires an initial margin of around $9000 while the price of one share of US OIL ETF is currently around $50. The lower minimum initial investment benefits small investors who are not able to hedge with derivatives on account of the large initial investment margin required by traditional commodity futures. Those investors can just link their future returns to commodity prices through specific ETFs to hedge against price fluctuation of commodities, purchasing and selling hedging components in small increments.

Although ETFs provide a convenient method for both large and small investors to hedge against commodity price fluctuations, few studies have explored the hedging effectiveness of commodity ETFs. Most of the previous research studies the performance measures of ETF or the comparison of performance measures between ETF and mutual funds. For example, Aber, Li and Can (2009) compare the tracking error of their sample

ETFs to that of the corresponding index mutual funds between 2000 and 2006. The objective of this thesis is to bridge this gap. However, its scope is limited to focusing on energy ETFs. I use data from all energy ETFs listed on US stock exchanges and London stock exchanges with the requirement that these ETFs initiated trading before 2008.

First, the Minimum Variance Hedge Ratio (MVHR) model is applied to estimate the optimal hedge ratios using in-sample data. Under the MVHR model, the measure of risk is the variance of the hedged portfolio. In earlier applications of the MVHR model, the variance of changes in the spot price of crude oil and the changes in the price of the hedging instrument were assumed to be constant. This assumption of constant variance is relaxed by applying a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach to estimate the conditional variance of the changes in the spot price of crude oil as well as the hedging instrument and thus the optimal hedge ratio. Note that the MVHR model focuses on the variance of the changes in the value of the hedged portfolio as a measure of risk. In contrast, the value at risk (VaR) of a portfolio is the maximum loss that could be expected to occur over a particular horizon with a given confidence level. The conditional value at risk (CVaR) is the expected loss on the portfolio, given that the loss exceeds VaR. While it is usual to assume that the changes in the value of the portfolio follows a normal distribution in estimating VaR and CVaR, modified value at risk (MVaR) takes into account the skewness and kurtosis of the probability density function of the changes in the value of the portfolio. Using VaR, CVaR and MVaR of the changes in the value of the hedged portfolio of crude oil and the energy ETF in turn as the measure of risk, I estimate optimal hedge ratios and hedging effectiveness by minimizing VaR, CVaR and MVaR respectively. Under the MVHR model, the hedging effectiveness measure is the proportionate reduction in risk achieved by using the hedging instrument. Similarly, I use the proportionate reduction in the VaR, CVaR and MVaR respectively, to measure hedging effectiveness with these three measures of risk.

This thesis is structured as follows; Chapter II presents a literature review. Chapter III and IV describe the data and methodology, respectively. Chapter V interprets the empirical results and Chapter VI summarizes the conclusions.

Chapter II. Literature Review

Physical Versus Synthetic ETFs and Commodity ETFs

ETFs are stock-featured funds which can be traded on stock exchanges. Basically, ETFs can be classified into physical ETFs and synthetic ETFs. Physical ETFs' asset allocation is related to the components of their underlying benchmark. For example, an equity-based ETF can hold all or part of the stocks of one underlying equity index for replicating the benchmark. The merits of a physical replication strategy include greater transparency of the ETF's asset holdings and more certainty of entitlement for investors once the ETFs are liquidated (Kosev and Williams, 2011). Synthetic ETFs refer to those ETFs which hold derivatives such as futures, forwards and options in their portfolio. Moreover, synthetic ETFs have lower costs as they do not need to rebalance their portfolio each time their index is changed or reweighted. Like futures, commodity ETFs do not require the investors to buy and store the physical commodities. The return of synthetic ETFs consists of three parts: the change in the price of the futures contract on the commodity, the rollover yield and the interest earned on collateral. The rollover yield refers to the yield obtained by rolling over the front month futures into the next month. Interest on collateral is produced from the cash value of the initial investment.

Most commodity ETFs in Europe are built as Exchange Traded Commodities (ETC) (Kosev and Williams, 2011). The ETC market was initiated in 2003 with the first gold product, Gold Bullion Securities. By 2007, the number of ETC products over the world increased from 10 to over 80 (Biekowski, 2007). Generally speaking, ETCs are set up to track the performance of a single commodity or to track the performance of underlying commodity indices (i.e. energy index, agricultural products index), so they function like ETFs. The single commodity ETC follows the spot price of one commodity whereas index-tracking ETCs follow the performance of an underlying commodity index (London Stock Exchange, 2009). ETCs have low correlation to equities and bonds, leading to reduced risks without reducing returns (London Stock Exchange, 2009). Despite different regulation and disclosure requirements, both ETFs and ETCs are listed and traded in similar ways so that I consider ETCs in my sample as well.

Most of the previous research, however, studies the performance measures of ETF or the comparison of performance measures between ETFs and mutual funds. Kostovetsky (2003) claims the main differences between ETFs and index mutual funds are the management fees, transaction fees, and taxation efficiency. Aber, Li and Can (2009) compare the tracking error of a sample ETF to that of the index mutual funds which have the same index as the ETF has between 2000 and 2006. They find that both ETF and the index mutual funds correlate their corresponding indices to almost the same extent. Rompotis (2009a) examines the performance of ETFs and index mutual funds, both of which are sponsored by the same fund manager such as Vanguard, in order to examine the interfamily competition. He finds that ETFs and index mutual funds have similar returns, volatility and low tracking errors. Besides, they both underperform their benchmark because of expenses and fees.

Models of Hedging

The main principle of hedging is to build a portfolio combining the spot market and futures market to reduce price volatility of a certain commodity. A portfolio consisting of C_s units of a long spot position and C_f units of a short futures position is considered a hedged portfolio as futures contracts are used to fix the price in the future. The return on the hedged portfolio is described as follows:

$$R_h = \frac{C_s\, S_t\, R_s - C_f\, F_t\, R_f}{C_s S_t} = R_s - hR_f \tag{1}$$

where

h $= C_f\, F_t\, / C_s S_t$;

$R_s = (S_{t+1} - S_t\,)/S_t$;

$R_f = (F_{t+1} - F_t\,)/F_t$;

S_t : spot price at time t;

F_t : futures price at time t;

R_s and R_f are the one-period of return on spot and futures positions, respectively and h is the hedge ratio, a ratio of the value of purchased or sold futures contracts to the value of commodities in the spot market.

The earliest model which applied portfolio theory to estimate the optimal hedge ratio is the minimum variance hedge ratio (MVHR) (Ederington, 1979; Johnson, 1960; Myers, Thompson, 1989) model. The MVHR model is easy to understand and apply in practice. It, however, ignores the expected return of the hedged portfolio and therefore it is not consistent with the mean-variance framework unless investors focus only on risk or unless the price of the hedging instrument (energy ETFs price in our case) strictly follows a martingale process (Chen, et al., 2003). In earlier applications of the MVHR model, the hedge ratio is a static one, which means that the hedge ratio would not be revised during the hedging period. However, new information or news that arrives in the market may affect hedging strategies. Accordingly, the optimal hedge ratio should change over time. ARCH and GARCH models, which are based on conditional distributions, are used to estimate dynamic time-varying hedge ratios. Baillie and Myers (1991) use daily data to examine six different commodities, beef, coffee, corn, cotton, gold and soybeans over two futures contract periods and find that a dynamic hedging strategy outperforms the static hedging strategy. Park and Switzer (1995) examine three stock index futures contracts in North America, comparing hedging performances of both stationary models based on Ordinary Least Squares (OLS) regression, OLS with cointegration and dynamic models such as bivariate GARCH. They conclude that the dynamic hedging strategy improves hedging performance over that of the traditional static hedging strategies.

Cao, Harris and Shen (2010) point out that MVHR is appropriate with respect to risk reduction only when investors have quadratic utility or when returns are elliptically distributed. When the above two assumption is not satisfied, variance is not the optimal measure of risk since it ignores the skewness and kurtosis of the return distribution.

Accordingly, new measures of risk emerge. Some studies have revealed that portfolio managers care about losses more than gains. Bawa (1975) proposes lower partial moments to measure downside risks. Thereafter, a number of models that measure downside risk have been proposed. For example, Lien et al. (2001) and Lien & Tse (2000) find the optimum hedge ratio by minimizing the hedged portfolio's generalized semivariance (GSV), which also considers stochastic dominance. These authors find that traditional mean variance hedging strategies are not efficient if portfolio managers only care about downside risk.

The Value at Risk approach was first introduced by J. P. Morgan in the 1990s and adopted by the Basle Committee to determine the minimum regulatory capital of banks (Alexander, Baptista, 2006). VaR now has been widely used as a risk management tool by many financial institutions. Referring to the definition of VaR (Jorion, 2000), Hung, Chiu and Lee(2006) provide an alternative hedging method by using a zero- VaR approach to measure downside risks of the hedged portfolio and they also derive a zero-VaR hedge ratio. After deriving the hedge ratio based on zero-VaR approach, they compare the zero-VaR hedge ratio to the MVHR hedge ratio. They conclude that as the risk-aversion level of investors increases, the zero-VaR hedge ratio converges to the MVHR, while if investors only care about downside risk, the zero-VaR hedge ratio may be completely different from the MVHR. In that case, the hedging strategy that minimizes the variance of the hedged portfolio becomes inappropriate. Cao, Harris and Shen (2010) derive the minimum-VaR and minimum-CVaR hedge ratios by using a semi-parametric method based on the Cornish-Fisher expansion. The new approach is applied to four equity index positions associated with equity index futures. They find that the semi-parametric method of estimating the minimum-VaR and minimum-CVaR is superior to the minimum variance approach and results in greater reduction in VaR and CVaR. Favre and Galeano (2002) modify the VaR approach, take into account the skewness and kurtosis of the return distribution and propose a new approach called the Modified Value at Risk (MVaR) approach to calculate the optimal hedge ratio by minimizing the MVaR at a given confidence level. The advantage of the MVaR approach over the VaR approach is that it is not based on any distribution assumption, therefore non-normal distribution of portfolio returns will not affect the hedging performance. They find that compared to the benefits of using the risk measures of VaR and the variance, the benefits of using the risk measure of MVaR would be higher if the portfolio has negative skewness or a positive kurtosis.

Chapter III. Data

Daily closing prices of ETFs and crude oil are obtained from Bloomberg. The daily total returns for each ETF are calculated as the percentage change in daily closing prices. The sample period covers the period from the date of inception of each ETF to January 11, 2012. For example, ProShares Ultra Oil & Gas Fund (DIG) started trading in 2007 while PowerShares Dynamic Oil & Gas Service Portfolio Fund (PXJ) commenced trading in 2006. I pool all of the energy ETFs together to construct the panel data. In order to have a long enough period time of data, only those ETFs that started trading at least from 2008 are selected. Table 1 shows the list of the ETFs used in this study along with information on their inception date, their investment strategies and their main holdings. Based on the ETFs' investment strategy and top holdings, I categorize these ETFs into four categories.

The first category, Stock-based ETFs, includes energy index ETFs, which attempt to track, before fees and expenses, the daily performance of some energy indices such as Dow Jones US Oil and Gas index. Basically, the portfolios of ETFs in this category mainly consist of energy corporations' stocks. The second category, Derivative-based ETFs, includes synthetic ETFs, the asset allocation of which includes crude oil or natural gas futures contracts or swaps. The percentage change in price of these ETFs is intended to reflect the percentage changes in the price of crude oil, heating oil or other energy commodity which is tracked by the changes in the price of the futures contract. The third category, Derivative-based ETCs, includes ETCs that hold futures contracts or forwards just as Derivative-based ETFs do. However, these ETCs are traded on the London Stock Exchange. I consider these ETCs separately since differences in the rules and regulations that govern ETFs in the U.S. and the U.K. may affect their hedging performance. The fourth category, Single-commodity ETFs, consists of ETFs on a single commodity such as crude oil or natural gas. Stock-based ETFs contain 8 ETFs, Derivative-based ETFs contain 13 ETFs, Derivative-based ETCs contain 8 ETCs and Single-commodity ETFs contain 19 ETFs. Finally, the daily return on an equal weighted portfolio of the 48 ETFs included in the study is also calculated for the sample period.

Table 2 provides descriptive statistics of the returns on the 48 ETFs as well as returns on crude oil. These statistics include the minimum, the maximum, and the first four moments of the return distribution (mean, standard deviation, skewness and kurtosis). Table 2 shows that the mean returns of these four categories of energy ETFs are lower than the mean return of the spot price of crude oil. Except for Derivative-based ETCs, whose portfolios include futures and swaps etc., the standard deviation of the returns of the other ETF categories is higher than the standard deviation of returns on crude oil. Derivative-based ETCs have the highest mean return and the lowest standard deviation, which suggests that the Derivative-based ETCs have the lowest risks. The positive median and skewness of Derivative-based ETCs reveals that the probability of positive return is higher than for the other three categories.

As it is shown in Table 2, the skewness and kurtosis of both energy ETFs and spot crude oil are significantly different from 0 and 3, respectively. The Kolmogorov-Smirnov test is applied to test for normality of the returns on the ETFs and on crude oil. The p-values of the Kolmogorov-Smirnov statistics of the four categories and of crude oil are all below 0.01, which suggests that the assumption of normally distributed returns is rejected at the 99% confidence level. These deviations from normally distributed returns imply that the Modified VaR model should be a more appropriate specification.

Table 1: Descriptive of each ETF

Type	Ticker	Name	Inception Date	Strategies	Top Holdings
Stock-based ETF	DIG US Equity	ProShares Ultra Oil and Gas	2/2/2007	Seek daily investment results twice the daily performance of the Dow Jones US Oil & Gas Index	Exxon Mobil; Chevron; ConocoPhillips
Stock-based ETF	ENY US Equity	Claymore/SWM Canadian Energy Income Index ETF	7/5/2007	Track the Sustainable Canadian Energy Income Index	Canadian Oil Sands Trust, Baytex Energy Trust; Suncor Energy Inc.
Stock-based ETF	FCG US Equity	First Trust ISE-Revere Natual Gas Index Fund	5/16/2007	Track "ISE-Revere Natural Gas IndexTM"	PetroQuest Energy, Inc.; Pioneer Natural Resources Company; Forest Oil Corporation
Stock-based ETF	IEO US Equity	Ishares Dow Jones U.S. Oil & Gas Exploration & Production Index Fund	5/8/2006	Track "Dow Jones US Select Oil Exploration & Production Index"	Occidental Peroleum Corp; Apache Corp; Anadarko Petroleum Corp
Stock-based ETF	IEZ US Equity	Ishares Dow Jones U.S. Oil Equipment Index	5/8/2006	Track"Dow Jones US Select Oil Equipment & Service Index"	Schlumberger LTD; Halliburton Co; National OilIll Varco Inc
Stock-based ETF	PXJ US Equity	PoIrshares Dynamic Oil&Gas Service Portfolio ETF	10/27/2005	Track" Oil & Gas Services Intellidex index"	Halliburton Co.; National OilIll Varco Inc.; Schlumberger Ltd.
Stock-based ETF	XES US Equity	SPDR S&P Oil & Gas Equipment & Services	6/23/2006	Track"S&P Oil & Gas Equipment & Services Select Industry Index"	Schlumberger Ltd. ; Halliburton Co; National OilIll Varco Inc.
Stock-based ETF	XOP US Equity	SPDR S&P Oil & Gas Exploration & Production ETF	6/23/2006	Track"S&P Oil & Gas Exploration & Production Select Industry Index"	Exxon Mobil Corp; Chevron Corp New; Conocophillips
Derivative-based ETF	DDG US Equity	First Trust ISE-Revere Natual Gas Index Fund	6/19/2008	Seek daily investment results inverse of the daily performance of the Dow Jones US Oil & Gas Index	DJUSEN Swaps

Derivative-based ETF	DUG US Equity	UltraShort Oil &Gas Proshares	2/2/2007	Seek daily investment results twice the inverse daily performance of the Dow Jones US Oil & Gas Index	DJUSEN Swaps
Derivative-based ETF	DBO US Equity	PoIrShares DB Oil Fund	1/8/2007	Track "Deutsche Bank Liquid Commodity Index"	WTI Crude Oil Futures contract
Derivative-based ETF	HND CN Equity	Horizons BetaPro NYMEX Natural Gas Bear Plus ETF	1/17/2008	Seek daily investment results equal to 200% the daily performance or inverse daily performance of NYMEX Natural Gas futures contract	NYMEX natural gas futures contract
Derivative-based ETF	HNU CN Equity	Horizons BetaPro NYMEX Natural Gas Bull Plus ETF	1/17/2008	Seek daily investment results equal to 200% the daily performance or inverse daily performance of NYMEX Natural Gas futures contract	NYMEX natural gas futures contract
Derivative-based ETF	HOD CN Equity	Horizons Betapro NYMEX Crude Oil Bear Plus ETF	1/17/2008	Seek daily investment results equal to 200% the daily performance, or inverse daily performance, of the NYMEX light sIet crude oil futures contract	NYMEX light sIet crude oil futures contract
Derivative-based ETF	HOU CN Equity	Horizons BetaPro NYMEX Crude Oil Bull Plus ETF	1/16/2008	Seek daily investment results equal to 200% the daily performance of the NYMEX light sIet crude oil futures contract	
Derivative-based ETF	SCO US Equity	ProShares UltraShort DJ-AIG Crude Oil ETF	11/26/2008	Seek Daily investment results equal to twice the inverse of the performance of the Dow Jones-AIG Crude Oil Sub-index	CLH0 futures; DJ-UBS swap
Derivative-based ETF	UCO US Equity	ProShares Ultra DJ-AIG Crude Oil ETF	11/26/2008	Seek Daily investment results equal to twice the performance of the Dow Jones-AIG Crude Oil Sub-index	CLH0 futures; DJ-UBS swap
Derivative-based ETF	UGA US Equity	United States Gasoline Fund	2/28/2008	Track in percentage terms the movements of gasoline prices	Gasoline Futures; US treasuries
Derivative-based ETF	UHN US Equity	United States Heating Oil Fund	4/10/2008	Track in percentage terms the movements of heating oil prices	Heating oil futures and other heating oil

					interests; US treasuries
Derivative-based ETF	UNG US Equity	United States Natural Gas Fund	4/19/2007	Track in percentage terms the movements of natural gas prices	
Derivative-based ETF	USO US Equity	United States Oil Fund	4/11/2006	Track the movements of light, sIet crude oil	oil futures and other oil interests; US treasuries
Derivative-based ETC	OILB LN Equity	ETFS Brent Oil ETF	7/29/2005	Track ICE futures brent contracts with an average maturity of one month	ETFS brent 1 month
Derivative-based ETC	OILW LN Equity	ETFS WTI Oil ETF	5/12/2006	Track NYMEX WTI oil contracts with an average maturity of two month	ETFS brent 2 months
Derivative-based ETC	OSB1 LN Equity	ETFS Brent 1yr ETF	8/16/2007	Track December ICE Futures Brent oil contracts with an average maturity of one year	ETS Brent 1 year
Derivative-based ETC	OSB2 LN Equity	ETFS Brent 2yr ETF	8/15/2007	Track December ICE Futures Brent oil contracts with an average maturity of two years	ETS Brent 2 year
Derivative-based ETC	OSB3 LN Equity	ETFS Brent 3yr ETF	8/17/2007	Track December ICE Futures Brent oil contracts with an average maturity of three years	ETS Brent 3 year
Derivative-based ETC	OSW1 LN Equity	ETFS WTI 1yr ETF	8/16/2007	Track NYMEX WTI oil contracts with an average maturity of one year	ETFS WTI 1 year
Derivative-based ETC	OSW2 LN Equity	ETFS WTI 2yr ETF	8/16/2007	Track NYMEX WTI oil contracts with an average maturity of two years	ETFS WTI 2 year2
Derivative-based ETC	OSW3 LN Equity	ETFS WTI 3yr ETF	8/16/2007	Track NYMEX WTI oil contracts with an average maturity of three years	ETFS WTI 3 year3
Single-commodity ETF	AIGO LN Equity	ETFS Petroleum ETF	9/29/2006	Track the DJ-AIG Petroleum Sub-Index	Crude oil(WTI); Unleaded Gasoline; Heating Oil
Single-commodity ETF	CRUD LN Equity	ETFS Crude Oil ETF	9/29/2006	Track the DJ-AIG Crude Oil Sub-Index	Crude oil(WTI)

Single-commodity ETF	FPET LN Equity	ETFS Forward Petroleum ETF	10/12/2007	Track the DJ-UBS Petroleum Sub-index	Crude oil(WTI); Unleaded Gasoline; Heating Oil
Single-commodity ETF	HEAF LN Equity	ETFS Forward Heating Oil ETF	11/30/2007	Track the DJ-UBS Heating Oil Sub-index	Heating oil
Single-commodity ETF	HEAT LN Equity	ETFS Heating Oil ETF	9/29/2006	Track the DJ-UBS Heating Oil Sub-index	Heating oil
Single-commodity ETF	LGAS LN Equity	ETFS Leveraged Gasoline ETF	3/12/2008	Seek daily investment results twice the daily performance of the DJ-UBS Gasoline Sub-index	Unleaded Gasoline
Single-commodity ETF	LHEA PZ Equity	ETFS Leveraged Heating Oil ETF	9/23/2008	Seek daily investment results twice the daily performance of the DJ-UBS Heating Oil Sub-index	Heating Oil
Single-commodity ETF	LNGA LN Equity	ETFS Leveraged Natural Gas ETF	3/12/2008	Seek daily investment results twice the daily performance of the DJ-UBS Natural Gas Sub-index	Natural Gas
Single-commodity ETF	LOIL LN Equity	ETFS Leveraged Crude Oil ETF	3/12/2008	Seek daily investment results twice the daily performance of the DJ-UBS Crude Oil Sub-index	Crude Oil (WTI)
Single-commodity ETF	LPET LN Equity	ETFS Leveraged Petroleum ETF	3/12/2008	Seek daily investment results twice the daily performance of the DJ-UBS Petroleum Sub-index	Crude oil(WTI); Unleaded Gasoline; Heating Oil
Single-commodity ETF	NGAF LN Equity	ETFS Forward Natual Gas ETF	11/30/2007	Track the DJ-AIG Natural Gas sub-index	Natural Gas
Single-commodity ETF	NGAS LN Equity	ETFS Natural Gas ETF	9/29/2006	Track the DJ-AIG Natural Gas sub-index	Natural Gas
Single-commodity ETF	NGSP LN Equity	ETFS Natural Gas Sterling ETF	10/30/2007	Track the DJ-AIG Natural Gas sub-index	Natural Gas
Single-commodity ETF	SGAS LN Equity	ETFS Short Gasoline ETF	2/25/2008	Seek daily investment results inverse the daily performance of the DJ-UBS Gasoline Sub-index	Unleaded Gasoline

Single-commodity ETF	SHEA LN Equity	ETFS Short Heating Oil ETF	2/25/2008	Seek daily investment results inverse the daily performance of the DJ-UBS Heating Oil Sub-index	Heating Oil
Single-commodity ETF	SNGA LN Equity	ETFS Short Natural Gas ETF	2/25/2008	Seek daily investment results inverse the daily performance of the DJ-UBS Natural Gas Sub-index	Natural Gas
Single-commodity ETF	SOIL LN Equity	ETFS Short Crude Oil ETF	2/25/2008	Seek daily investment results inverse the daily performance of the DJ-UBS Crude Oil Sub-index	Crude Oil(WTI)
Single-commodity ETF	SPET LN Equity	ETFS Short Petroleum ETF	2/25/2008	Seek daily investment results inverse the daily performance of the DJ-UBS Petroleum Sub-index	Crude oil(WTI); Unleaded Gasoline; Heating Oil
Single-commodity ETF	UGAS LN Equity	ETFS Gasoline ETF	9/29/2006	Track the DJ-UBS Unleaded Gasoline Sub-index	Unleaded Gasoline

Table 2: Descriptive Statistics of returns on ETFs and crude oil

	Minimum	Mean	Median	Standard Deviation	Maximum	Skewness	Kurtosis	Kolmogorov-Smirnov
Panel A: ETFs								
Stock-based ETFs	-0.3155	0.0005	0.0014	0.0301	0.3629	-0.1899	9.5972	0.0763***
								(<0.0100)
Derivative-based ETFs	-0.3656	-0.0004	-0.0002	0.0407	0.3176	-0.0377	4.8217	0.0707***
								(<0.0100)
Derivative-based ETCs	-0.2282	0.0005	0.0012	0.0200	0.3444	0.8201	21.4509	0.0679***
								(<0.0100)
Single-commodity ETFs	-0.3687	-0.0005	0.0000	0.0319	0.5385	0.6216	14.6001	0.0766***
								(<0.0100)
Panel B								
Crude Oil	-0.1225	0.0005	0.0012	0.0281	0.2371	0.3772	5.3506	0.0605***
								(<0.0100)

*** statistically significant at the 99% confidence level.

Chapter IV. Methodology

I describe previous research in which spot price fluctuations were hedged using futures contracts. I apply this research to determine the hedging effectiveness of energy ETFs in hedging crude oil fluctuations. In this application, the energy ETF is the hedging instrument and takes the place of the futures contract in previous research. Accordingly, in this application of these models, the change in the futures price is replaced by the change in the price of the ETFs which are used to hedge.

Minimum Variance Hedge Ratio Model

Ederington (1978) derives the MVHR by minimizing the portfolio's risk, which is proxied by the variance of the portfolio's returns. The objective function is described as follows:

$$
\begin{aligned}
Minimize\ Var(V_h) &= var(\Delta S - h\Delta F) \\
&= \sigma_{\Delta s}^2 + h^2\sigma_{\Delta f}^2 - 2h\sigma_{\Delta s,\Delta f} \qquad (2)
\end{aligned}
$$

with respect to h

where

ΔS: change in the spot price;

ΔF: change in the futures price;

$\sigma_{\Delta s}^2$: variance of the change in the spot price;

$\sigma_{\Delta f}^2$: variance in the change in the futures price;

$\sigma_{\Delta s,\Delta f}$: covariance between the change in the spot price and the change in the futures price;

h: hedge ratio, which is the number of units of futures for each unit of the spot commodity.

The optimal hedge ratio is obtained as:

$$h^{MV} = \frac{\sigma_{\Delta s,\Delta f}}{\sigma_{\Delta f}} = \rho \times \frac{\sigma_{\Delta s}}{\sigma_{\Delta f}} \tag{3}$$

where

ρ: correlation between the change in spot price and the change in the futures price.

There exist abundant techniques to estimate the optimal hedge ratios.

Estimation of the optimal hedge ratio using ordinary least squares

The conventional approach is to use an ordinary least squares (OLS) regression. Junkus and Lee (1985) regress changes in spot prices on the corresponding changes in futures prices, using a simple linear regression to estimate the hedge ratio. The regression is specified as follows:

$$\Delta S_t = a_0 + a_1 \Delta F_t + e_t \tag{4}$$

where a_1 is the estimated hedge ratio, ΔS_t is the change in the spot price at time t, ΔF_t is the corresponding change in the futures price and e_t is the error term. Although an OLS regression is simple to apply, if the assumption of homoscedasticity of the error term is not satisfied, the hedge ratio will be biased. To address the issue of heteroscedaticity, an issue of inconstant error term in the regression, a GARCH model, which allows the hedge ratio to change over time as well, is strongly recommended.

Estimation of the optimal hedge ratio using GARCH

As new information arrives in the market, the variance of spot and futures prices could change. Therefore, hedge ratios would change over time.

The GARCH model mainly includes five equations. The first two equations capture the conditional means of the distribution of spot price changes and futures price changes. The other three equations account for time-varying variances of spot price changes, variances of futures price changes and the covariance between spot and futures price changes. Bollerslev (1986) first proposed the GARCH(1,1) model, which was applied by Baillie and Bollerslev(1990) to estimate the joint distribution of spot and futures prices for six commodities, beef, coffee, corn, cotton, gold and soybeans.

The Bivariate GARCH VECH model (Baillie and Myers, 1999) is defined as follows:

$$\begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5}$$

and

$e_t|\Omega_{t-1} \sim \mathrm{N}(0, \boldsymbol{H}_t)$,

$\mathrm{VECH}(\boldsymbol{H}_t) = C + A \times \mathrm{VECH}(\boldsymbol{e}_{t-1} e_{t-1}^{'}) + B \times \mathrm{VECH}(\boldsymbol{H}_{t-1})$.

where

$\boldsymbol{H}_t$: 2×2 conditional variance-covariance matrix;

$\boldsymbol{e}_{t-1}$: 2×1 innovation vector;

Ω_{t-1}: information set at time t-1;

C: 3×1 parameter vector;

A and B: 3×3 parameter matrices.

A, B and C are all constant numbers which could be estimated by using historical data.

Brooks (2008) defines:

$$\boldsymbol{H}_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}, \boldsymbol{e}_t = \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}, \ \mathrm{C} = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{31} \end{bmatrix}$$

$$\mathrm{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \mathrm{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

where

h_{iit} : conditional variance at time t of the spot price change(i=1) and futures price change (i=2);

h_{ijt} (i≠j): conditional covariance between spot and futures price change.

The VECH model in full is described as follows:

$$h_{11t=}c_{11} + a_{11}u_{1,t-1}^2 + a_{12}u_{2,t-1}^2 + a_{13}u_{1t-1}u_{2t-1} + b_{11}h_{11t-1} + b_{12}h_{22t-1} + b_{13}h_{12t-1} \quad (6)$$

$$h_{22t=}c_{21} + a_{21}u_{1,t-1}^2 + a_{22}u_{2,t-1}^2 + a_{23}u_{1t-1}u_{2t-1} + b_{21}h_{11t-1} + b_{22}h_{22t-1} + b_{23}h_{12t-1} \quad (7)$$

$$h_{11t=}c_{31} + a_{31}u_{1,t-1}^2 + a_{32}u_{2,t-1}^2 + a_{33}u_{1t-1}u_{2t-1} + b_{31}h_{11t-1} + b_{32}h_{22t-1} + b_{33}h_{12t-1} \quad (8)$$

In the two assets case, the unrestricted VECH model contains 21 parameters. As the number of assets included in the model increases, estimation of the unrestricted VECH model would become infeasible. Therefore, Bollerslev, Engle and Wooldridge (1988) restricted the conditional variance-covariance matrix $H_t$with diagonal A and B, each of which has 3 elements. The model, referred to as the diagonal VECH, is given by

$$h_{11t} = M_{11} + A_{11}u_{1,t-1}^2 + B_{11}h_{11,t-1} \quad (9)$$

$$h_{22t} = M_{22} + A_{22}u_{2,t-1}^2 + B_{22}h_{22,t-1} \quad (10)$$

$$h_{12t} = M_{12} + A_{12}u_{1,t-1}u_{2,t-1} + B_{12}h_{12,t-1} \quad (11)$$

The hedge ratio is given by

$$h_{t-1}^{GARCH} = \frac{h_{12,t}}{h_{22,t}} \quad (12)$$

M_{ij}, A_{ij}, B_{ij} $(i, j = 1,2)$ are parameters to be estimated. This diagonal VECH model, however, cannot ensure a positive semi-definite covariance matrix, which means the variance and covariance could become negative.

Models based on Value at Risk

Measure of risk is VaR

A portfolio's VaR is the maximum loss that the investor would expect to suffer over a certain period at a given confidence level. The original formula for a portfolio w's VaR is V (α, r) =- F_w^{-1}(α), where r is the return on the portfolio w, α is the confidence level and $F_w^{-1}(.)$ is the cumulative distribution function(cdf) of the return on the portfolio. The portfolio return is often assumed to be normally distributed (Hull and White, 1998, Jackon et al., 1997). Duffie and Pan (1997) assert that fat tails may be less critical for a well-diversified portfolio, although they may be important for a portfolio consisting of a single asset. Based on the assumed normal distribution of portfolio returns, portfolio w's VaR at a given probability of 1-α in a certain period is as follows:

$$\text{VaR} = -(r_i + z_\alpha \sigma_i) \quad (13)$$

where

z_α: αth percentile of the standard normal distribution;

r_i: return of the portfolio;

σ_i: standard deviation of the portfolio return.

α is the confidence level, which can be considered as the risk aversion parameter. For example, if the portfolio managers prefer to take more risks, a lower confidence level can be chosen. On the other hand, a higher confidence level can be used if the portfolio managers are more risk averse.

I need to minimize VaR to find the optimal hedge ratios. Therefore, the objective function is represented as follows:

$$\text{Minimize } VaR(r_h) = -(\,E(r_h) + z_\alpha \sigma_h) \tag{14}$$

with respect to h

where $E(r_h) = E(r_{oil}) - hE(r_{ETF})$

$VaR(r_h)$: Value at Risk of the hedged portfolio;

$E(r_h)$: expected return of the hedged portfolio;

$E(r_{oil})$: expected return of crude oil;

$E(r_{ETF})$: expected return of the ETF;

σ_h: standard deviation of the return on the hedged portfolio;

h: hedge ratio.

z_α: αth percentile of the standard normal distribution.

In order to determine the optimal hedge ratio h, the first-order derivative of the objective function needs to be set equal to zero. First, Equation 13 is rearranged as follows:

$$\text{Min } VaR(r_h) = -[\mathrm{E}(r_{oil})) - \mathrm{hE}(r_{ETF})) + \mathrm{z}_\alpha(\sigma_{oil}^2 + h^2\sigma_{ETF}^2 - 2\mathrm{h}\sigma_{oil,ETF})^{0.5}] \qquad (15)$$

where

σ_{oil}^2: variance of the return on crude oil;

σ_{ETF}^2: variance of the return on ETF;

$\sigma_{oil,ETF}$: covariance between the returns on crude oil and of ETF;

Second, the first derivative of Equation 14 is taken and set to zero. With some algebraic manipulations, this results in:

$$\mathrm{E}(r_{ETF}) \text{- } 0.5\ \mathrm{z}_\alpha \frac{2h\sigma_{ETF}^2 - 2\sigma_{oil,ETF}}{\sqrt{\sigma_{oil}^2 + h^2\sigma_{ETF}^2 - 2\mathrm{h}\sigma_{oil,ETF}}} = 0 \qquad (16)$$

The optimal hedge ratio is then given by:

$$h^{VaR} = \rho\frac{\sigma_{oil}}{\sigma_{ETF}} - \mathrm{E}(r_{ETF})\frac{\sigma_{oil}}{\sigma_{ETF}}\sqrt{\frac{1-\rho^2}{z_\alpha^2\sigma_{ETF}^2 - r_{ETF}^2}} \qquad (17)$$

ρ is the correlation coefficient between the returns on crude oil and on the ETF. The VaR based hedge ratio takes the expected return of the ETF and the portfolio managers' risk preference into account. However, it is based on the assumption that portfolio returns are normally distributed, which could result in an underestimation of downside risk and an overestimation risk-adjusted performance (Eling, M., 2008). Hedge ratios based on Modified Value at Risk (MVaR) avoids this problem since it considers the skewness and kurtosis of the returns of the hedged portfolio.

Measure of risk is CVaR

A shortcoming of VaR is that it does not consider losses in excess of VaR, which could occur. Besides, VaR is not a coherent measure of risk unless the return of portfolio follows a normal distribution (Rockafellar and Uryasev, 2000). In general, a risk measure is considered as a coherent risk measure if it satisfies the properties of normalized, monotonicity, sub-additivity, positive homogeneity and translation invariance (Rockafellar and Uryasev, 2000). For example, the property of normalized means that investors will not face any risk if they hold no assets. The property of sub-additivity refers that the risk of holding a portfolio including two assets could not be greater than the risk of holding only one asset because of risk diversification. However, VaR of a combination of two portfolios could be greater than the sum of the VaRs of each individual portfolio. Therefore, VaR is not a coherent measure of risk. Compared with VaR, Conditional Value at Risk is considered as a better measure of risk as Pflug (2000) has shown that CVaR is coherent. The CVaR is defined as the expected loss over a given time period at a given confidence level given that the loss exceeds VaR.

Min CVaR $= \mathrm{E}(-r_{it} \mid -r_{it} \leq -VaR_i)$ (Agarwal and Naik, 2004) (18)

where

r_{it}: return of the hedged portfolio at time t;

VaR : value at risk of the return of the hedged portfolio.

Chi, Zhao and Yang(2009) simplify Equation (18) as follows:

$$\mathrm{CVaR(h)} = -\frac{\frac{1}{\sqrt{2\pi}} e^{-\frac{(\emptyset^{-1}(\alpha))^2}{2}}}{\alpha} \sigma_h - E(r_h)$$

$$=hE(r_{ETF})-E(r_{oil})-\frac{\frac{1}{\sqrt{2\pi}}e^{-\frac{(\emptyset^{-1}(\alpha))^2}{2}}}{\alpha}\sqrt{\sigma_{oil}^2+h\sigma_{ETF}^2-2h\sigma_{oil,ETF}} \tag{19}$$

where

σ_h: standard deviation of the hedged portfolio;

$E(r_h)$: expected return of the hedged portfolio;

$E(r_{ETF})$: expected return of ETF;

$E(r_{oil})$: expected return of crude oil;

σ_{oil}^2: variance of the return on crude oil;

σ_{ETF}^2: variance of the return on ETF;

$\sigma_{oil,ETF}$: covariance between the returns on crude oil and of ETF;

h: hedge ratio;

$\emptyset^{-1}(.)$: standard normal cdf.

α: confidence level.

They then determine the hedge ratio which minimizes CVaR to be:

$$h^{CVaR}=\rho\frac{\sigma_{oil}}{\sigma_{ETF}}-E(r_{ETF})\frac{\sigma_{oil}}{\sigma_{ETF}}\sqrt{\frac{1-\rho^2}{k_\alpha^2\sigma_{ETF}^2-r_{ETF}^2}} \tag{20}$$

where

$$k_\alpha=-\frac{\frac{1}{\sqrt{2\pi}}e^{-\frac{(\emptyset^{-1}(\alpha))^2}{2}}}{\alpha};$$

ρ : correlation between the returns on crude oil and one the ETF.

Measure of risk is MVaR

As traditional VaR only considers the first two moments (mean and standard deviation) of a distribution, the risk estimated by VaR model may be biased if the distribution has a fat tail. Favre and Galeano (2002) propose a method called Modified Value at Risk (MVaR) to measure the risk of a portfolio with non-normally distributed returns. Modified Value at Risk (MVaR) takes into account the skewness and kurtosis of the return on the portfolio as well as the expected return and standard deviation of return on the portfolio. Gregoriou and Gueyie (2003) claim that MVaR is a better measure to investigate extremely negative returns and non-normally distributed returns of portfolios because MVaR considers skewness and kurtosis of a distribution. Using MVaR as a measure of risk, the objective function becomes:

$$\text{Min MVaR} = -\{\mathrm{E}(r_h) + \sigma_h \left[z_\alpha + \frac{(z_\alpha^2 - 1)S_i}{6} + \frac{(z_\alpha^3 - 3z_\alpha)E_i}{24} - \frac{(2z_\alpha^3 - 5z_\alpha)S_i^2}{36} \right]\} \tag{21}$$

with respect to h

where

$\mathrm{E}(r_h) = \mathrm{E}(r_{oil}) - \mathrm{h}E(r_{ETF})$

$\sigma_h^2 = \sigma_{oil}^2 + h^2\sigma_{ETF}^2 - 2\mathrm{h}\sigma_{oil,ETF}$

$\mathrm{E}(r_h)$: expected return of the hedged portfolio;

$\mathrm{E}(r_{oil})$: expected return of crude oil;

z_α : αth percentile of the standard normal distribution;

σ_{oil} : standard deviation of the return on crude oil;

σ_{ETF} : standard deviation of the return on the ETF;

$\sigma_{oil,ETF}$: covariance between the returns on crude oil and on the ETF;

S_i: skewness of the return on the hedged portfolio;

E_i: kurtosis of the return on the hedged portfolio;

The optimal hedge ratio which minimizes MVaR is given by:

$$h^{MVaR} = \rho \frac{\sigma_{oil}}{\sigma_{ETF}} - \mathrm{E}(\mathrm{r}_{ETF}^{\alpha}) \frac{\sigma_{oil}}{\sigma_{ETF}} \sqrt{\frac{1-\rho^2}{\left[z_\alpha+(z_\alpha^2-1)*\frac{S_i}{6}+(z_\alpha^3-3z_\alpha)*\frac{E_i}{24}-(2z_\alpha^3-5z_\alpha)*\frac{S_i^2}{36}\right]^2 \sigma_{ETF}^2 - r_{ETF}^2}} \tag{22}$$

where

ρ : correlation between the returns on crude oil and on the ETF.

<u>Hedging Effectiveness Measures</u>

Ederington (1979) defines the hedging effectiveness of a futures contract as:

$$\mathrm{HE}^{\mathrm{variance}} = 1 - \frac{\mathrm{Variance}_{\mathrm{hedged}}}{\mathrm{Variance}_{\mathrm{unhedged}}} \tag{23}$$

where

$\mathrm{Variance}_{\mathrm{hedged}}$=variance of the change in value of the optimal hedged portfolio;

$\mathrm{Variance}_{\mathrm{unhedged}}$=variance of the change in value of the unhedged portfolio.

This hedging effectiveness measure has been extensively applied in the literature to evaluate hedging effectiveness (Floros and Vougas, 2008, 1991; Chen and Ford, 2010). The advantage of Ederington's measure is that it is simple to apply and interpret. There are, however, some disadvantages of this measurement. First, since it is based on the mean-variance approach to portfolio selection, it does not distinguish between upside and downside risks. Second, it is based on the implicit assumption that the hedged portfolio return is normally distributed, which may not always be the case.

Therefore, I use three other comparable measures to estimate the hedging effectiveness, the proportionate reduction in the VaR, CVaR and MVaR of the hedged portfolio. The corresponding hedging effectiveness measures are as follows:

$$HE^{VaR} = \frac{VaR_{unhedged} - VaR_{hedged}}{VaR_{unhedged}} \tag{24}$$

where

$VaR_{unhedged}$: VaR of the return on unhedged crude oil;

VaR_{hedged} : VaR of the return on hedged portfolio obtained by minimizing the VaR.

$$HE^{CVaR} = \frac{CVaR_{unhedged} - CVaR_{hedged}}{CVaR_{unhedged}} \tag{25}$$

where

$CVaR_{unhedged}$: CVaR of the return on unhedged crude oil;

$CVaR_{hedged}$: CVaR of the return on hedged portfolio obtained by minimizing the CVaR.

$$HE^{MVaR} = \frac{MVaR_{unhedged} - MVaR_{hedged}}{MVaR_{unhedged}} \tag{26}$$

where

$MVaR_{unhedged}$: MVaR of the return on unhedged crude oil;

$MVaR_{hedged}$: MVaR of the return on hedged portfolio obtained by minimizing the MVaR.

I break the dataset into two periods, the in-sample period and the out-of-sample period. The in-sample period is from the inception date of each ETF to December 31, 2009 and the out-of-sample period is from January 1, 2010 to January 11, 2012. For the OLS regression, the daily change in the crude oil prices is regressed on the change in the ETF price as in Equation (4) to estimate optimal hedge ratios under the MVHR model first by using in-sample data. The hedge ratios are derived from the slope coefficients in Equation

(4) and hedging effectiveness is estimated as the R-square of the regressions. Second, the estimated hedge ratios are applied to out-of-sample data to calculate the out-of-sample hedging effectiveness of each ETF (Equation 23). For the GARCH approach, the time-varying hedge ratio is estimated by using the in-sample data. After obtaining the estimated parameters of Equation (10) and Equation (11), I calculate the hedge ratio as it is shown in Equation (12) for each day and then calculate the in-sample hedging effectiveness. The estimated parameters from the in-sample period are applied to out-of-sample data to compute the conditional variance and covariance, hedge ratio and out-of-sample hedging effectiveness.

In applying the hedging models based on VaR, CVaR and MVaR, first, I use the in-sample data to estimate the optimal hedge ratios which minimize VaR, CVaR and MVaR, respectively. A confidence level of 95% is selected to reflect portfolio managers' risk preference. The optimal hedge ratio for each ETF is then used in equation (14), (18) and (21) to calculate the VaR, CVaR and MVaR of the hedged portfolio, respectively. Equations (24), (25) and (26) are applied to calculate hedging effectiveness, respectively for both periods.

However, the significance of differences in hedging effectiveness among these four categories of ETFs remains uncertain. Therefore, a t-test is conducted to examine whether the hedging effectiveness of each category is significantly different from those of the others. At a significance level of 0.1%, the critical value is 2.326. Therefore, if the t-statistics is less than 2.326, the null hypothesis of no difference between the hedging effectiveness of the categories will be rejected.

Chapter V. Empirical Results

Results of the MVHR model

Results based on OLS

The results reveal that Derivative-based ETFs have a superior hedging effectiveness in the in-sample period as they reduce the variance of the unhedged portfolio by 47.04%. Table 3 suggests that in the in-sample period, on average, the variance reduction, that is, the hedging effectiveness, achieved by using Derivative-based ETFs is significantly higher than that from Single-commodity ETFs. However, I cannot find a significant difference between the hedging effectiveness measures of Derivative-based ETFs and Stock-based ETFs and between Derivative-based ETFs and Derivative-based ETCs. The possible explanation for this result is that Derivative-based ETFs and Derivative-based ETCs incorporate hedging products, which have the same investment strategies but are traded in two different markets. With regard to the out-of-sample period, I find that Stock-based ETFs outperform the other ETFs in reducing risks by 37.49%. This result, however, is not consistent with the results from the in-sample period.

Table 3: In-sample comparison of Hedging Effectiveness based on OLS regression

	Variance_unhedged	Variance_hedged	Hedging Effectiveness
Stock-based ETFs	4.9784	3.3994	31.42%
Derivative-based ETFs	6.0317	3.3345	47.04%
Derivative-based ETCs	4.9344	3.1864	35.29%
Single-commodity ETFs	6.0497	4.4994	26.08%

Hedging Effectiveness: $HE^{\text{variance}} = 1 - \frac{\text{Variance}_{\text{hedged}}}{\text{Variance}_{\text{unhedged}}}$

Table 4: Comparison of hedging effectiveness based on the OLS regression for the different categories of ETFs: in-sample period

OLS	T statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-1.56	-1.12	1.05
	(0.1361)	(0.2817)	(0.3059)
Derivative-based ETFs		1.15	2.81***
		(0.2654)	(0.0086)
Derivative-based ETCs			1.72*
			(0.0984)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Table 5: Out-of-sample comparison of Hedging Effectiveness using OLS regression

	Variance_unhedged	Variance_hedged	Hedging Effectiveness
Stock-based ETFs	3.0351	1.8974	37.49%
Derivative-based ETFs	3.0451	1.9882	34.74%
Derivative-based ETCs	3.0670	1.9461	36.55%
Single-commodity ETFs	3.0551	2.3523	23.01%

Hedging Effectiveness: $HE^{variance} = 1 - \frac{Variance_{hedged}}{Variance_{un\,hedged}}$

Table 6: Comparison of hedging effectiveness based on the OLS regression for the different categories of ETFs: out-of-sample period

OLS	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single-commodity ETFs
Stock-based ETFs	0.25	0.32	2.37**
	(0.8091)	(0.755)	(0.0256)
Derivative-based ETFs		-0.16	1.38
		(0.8745)	(0.179)
Derivative-based ETCs			2.17**
			(0.0397)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Results based on the GARCH model

Table 7 and 8 present the in-sample and out-of-sample hedging effectiveness based on the application of the MVHR model using GARCH methodology, respectively. Compared with the unhedged portfolio, hedging with ETFs from any category helps reduce risks both in the in-sample as well as the out-of-sample periods. Basically, I draw the same conclusion as that from the application of OLS regression, that is, Derivative-based ETFs have the best hedging performance in in-sample period. In the out-of-sample period, I only find a statistically significant difference between the hedging effectiveness of Derivative-based ETFs and Single-commodity ETFs.

I examine whether application of the GARCH model is superior to application of OLS since the GARCH model allows variation in the variances and covariances over time. Comparing Table 3 with Table 7 and Table 5 with Table 9, I note that the measures of hedging effectiveness which result from application of the GARCH methodology are higher than those which result from application of OLS regression. For example, on using the GARCH model, Derivative-based ETFs lower the variance of the unhedged portfolio by 55.07% and 56.27% in the in-sample period and the out-of-sample period, respectively. On applying the OLS regression, 47.04% and 34.74% of the variance of the unhedged portfolio has been reduced in the in-sample period and out-of-sample period, respectively. The results indicate that a hedging strategy based on application of the bivariate GARCH model is superior to hedging based on application of OLS regression. However, the disadvantage of application of the GARCH methodology is that frequent rebalancing of the portfolio could result in high transaction costs.

Table 7: In-sample comparison of Hedging Effectiveness based on GARCH

	Variance_unhedged	Variance_hedged	Hedging Effectiveness
Stock-based ETFs	4.9784	3.3861	31.66%
Derivative-based ETFs	6.0317	2.8101	55.07%
Derivative-based ETCs	4.9344	3.1137	36.86%
Single-commodity ETFs	6.0497	4.1789	30.87%

Hedging Effectiveness: $HE^{variance} = 1 - \frac{Variance_{hedged}}{Variance_{unhedged}}$

Table 8: Comparison of hedging effectiveness based on the GARCH model for the different categories of ETFs: in-sample period

GARCH	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single-commodity ETFs
Stock-based ETFs	-2.47**	-2.45**	0.15
	(0.0232)	(0.0281)	(0.885)
Derivative-based ETFs		1.91*	3.31***
		(0.071)	(0.0025)
Derivative-based ETCs			1.1
			(0.2831)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Table 9: Out-of-sample comparison of Hedging Effectiveness based on GARCH

	Variance_unhedged	Variance_hedged	Hedging Effectiveness
Stock-based ETFs	3.0351	1.8531	38.94%
Derivative-based ETFs	3.0437	1.3320	56.27%
Derivative-based ETCs	3.0670	1.9101	37.73%
Single-commodity ETFs	3.0551	2.0690	32.29%

$$\text{Variance Reduction: } HE^{\text{variance}} = 1 - \frac{\text{Variance}_{\text{hedged}}}{\text{Variance}_{\text{unhedged}}}$$

Table 10: Comparison of hedging effectiveness based on the MVHR model for the different categories of ETFs: out-of-sample period

GARCH	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity based ETFs
Stock-based ETFs	-1.34	0.49	0.9
	(0.1947)	(0.6345)	(0.3758)
Derivative-based ETFs		1.44	2.41**
		(0.1661)	(0.0222)
Derivative-based ETCs			0.74
			(0.4669)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Results based on minimizing VaR

Table 11: In-sample comparison of Hedging Effectiveness based on VaR

	VaR_unhedged	VaR_hedged	Hedging Effectiveness
Stock-based ETFs	0.0611	0.0511	16.31%
Derivative-based ETFs	0.0716	0.0475	33.55%
Derivative-based ETCs	0.0603	0.0511	15.24%
Single commodity ETFs	0.0691	0.0587	15.13%

Hedging Effectiveness: $HE^{VaR} = \frac{VaR_{unhedged} - VaR_{hedged}}{VaR_{unhedged}}$

From Table 11, I note that in the in-sample period, hedging based on minimizing VaR is effective in reducing the VaR of the portfolio consisting of crude oil and energy ETFs for all four categories of ETFs. Derivative-based ETFs outperforms the other three groups with an in-sample hedging effectiveness of 33.55%, while Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs just have a hedging effectiveness of around 15%. Stock-based ETFs rank second in hedging effectiveness as this group has an in-sample hedging effectiveness of 16.39%. Table 12 describes the results of the t-test. I notice that only the hedging effectiveness of Derivative-based ETFs is significantly different from those of the other three categories. Although using Stock-based ETFs, Derivative ETCs and Single-commodity ETFs to hedge is much better than not-hedging, using ETFs from Derivative-based ETFs to hedge against crude oil price fluctuation is more effective than using ETFs from the other categories.

Table 12: Comparison of hedging effectiveness based on the VaR model for the different categories of ETFs: in-sample period

VaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-2.42**	0.53	0.41
	(0.0254)	(0.6022)	(0.6884)
Derivative-based ETFs		2.53**	3.65***
		(0.0205)	(0.001)
Derivative-based ETCs			0.03
			(0.9733)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Table 13 provides the out-of-sample hedging effectiveness. The results indicate that Derivative-based ETFs are most effective which is consistent with the results from the in-sample period, as the hedging effectiveness is 38.67% on average. Table 14, summarizing the output of the t-test, shows that the out-of-sample hedging effectiveness of Derivative-based ETFs is significantly different from those of the other categories. However, there is no significant difference between the hedging effectiveness of the other three categories of ETFs.

Table 13: Out-of-sample comparison of Hedging Effectiveness based on VaR

	VaR_unhedged	VaR_hedged	Hedging Effectiveness
Stock-based ETFs	0.0383	0.0300	21.50%
Derivative-based ETFs	0.0383	0.0235	38.67%
Derivative-based ETCs	0.0383	0.0304	20.63%
Single commodity based ETFs	0.0383	0.0310	18.99%

Hedging Effectiveness: $HE^{VaR} = \frac{VaR_{unhedged} - VaR_{hedged}}{VaR_{unhedged}}$

Table 14: Comparison of hedging effectiveness based on the VaR model for the different categories of ETFs: out-of-sample period

VaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-1.69	0.38	0.55
	(0.1074)	(0.7075)	(0.589)
Derivative-based ETFs		1.76*	2.67**
		(0.0952)	(0.0122)
Derivative-based ETCs			0.34
			(0.7338)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Results based on minimizing CVaR

From Table 15, we note that the hedging based on CVaR is effective in reducing the CVaR of the portfolio incorporating crude oil and energy ETFs for all four categories. Derivative-based ETFs outperform the other three groups with a hedging effectiveness of 29.45% while hedging using Stock-based ETFs, Derivative ETCs and Single-commodity ETFs just has a hedging effectiveness around 16%. Derivative-based ETCs are ranked second in hedging effectiveness as they reduce the VaR of the portfolio by 17.18%. From

Table 16, which presents the results of the t-test, I note that only the hedging effectiveness of Stock-based ETFs is significantly different from that of ETFs in the other three categories. Thus, using Derivative-based ETFs to hedge against crude oil price fluctuation is more effective than using ETFs from the remaining categories and the hedging performance of Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs are almost the same. Admittedly, using Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs to hedge is much better than not-hedging as the VaR of the hedged portfolio has been decreased by 16% on average.

Table 15: In-sample comparison of Hedging Effectiveness based on CVaR

	CVaR_unhedged	CVaR_hedged	Hedging Effectiveness
Stock-based ETFs	0.0821	0.0682	16.96%
Derivative-based ETFs	0.0907	0.0639	29.45%
Derivative-based ETCs	0.0816	0.0677	17.18%
Single commodity ETFs	0.0880	0.0744	15.54%

Hedging Effectiveness: $HE^{CVaR} = \frac{CVaR_{unhedged} - CVaR_{hedged}}{CVaR_{unhedged}}$

Table 16: Comparison of hedging effectiveness based on the CVaR model for the different categories of ETFs: in-sample period

CVaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-2.02*	-0.05	0.5
	(0.0572)	(0.963)	(0.6231)
Derivative-based ETFs		1.73*	3.1**
		(0.0991)	(0.0042)
Derivative-based ETCs			0.41
			(0.6868)

***indicates significance at 0.01 level;
** indicates significance at 0.05 level;
*indicates significance at 0.1 level.

Table 17 and 18 report the results of out-of-sample hedging effectiveness and results of t-tests. The results indicate that the reduction in CVaR of 48.66% achieved by using Derivative-based ETFs is ranked first in hedging effectiveness, which is consistent with the result from the in-sample period. The results of t-test show that the CVaR reduction achieved by using Derivative-based ETFs is significantly different from that achieved by using ETFs from the other categories, but it would not make much difference if we use Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs to hedge against crude oil price fluctuation.

Table 17: Out-of-sample comparison of Hedging Effectiveness based on CVaR

	CVaR_unhedged	CVaR_hedged	Hedging Effectiveness
Stock-based ETFs	0.0602	0.0411	31.70%
Derivative-based ETFs	0.0617	0.0317	48.66%
Derivative-based ETCs	0.0614	0.0425	30.72%
Single commodity ETFs	0.0621	0.0425	31.57%

$$\text{Hedging Effectiveness: } HE^{CVaR} = \frac{CVaR_{unhedged} - CVaR_{hedged}}{CVaR_{unhedged}}$$

Table 18: Comparison of hedging effectiveness based on the CVaR model for the different categories of ETFs: out-of-sample period

CVaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-2.22**	0.33	0.04
	(0.039)	(0.7433)	(0.972)
Derivative-based ETFs		2.27**	3.09***
		(0.035)	(0.0043)
Derivative-based ETCs			-0.22
			(0.8248)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Results based on minimizing MVaR

From Table 19, we can see that hedging based on MVaR is effective in reducing the MVaR of the portfolio of crude oil and energy ETFs for all four categories in the in-sample period. Stock-based ETFs outperform ETFs from the other three categories with a hedging effectiveness of 47.54%, while hedging by using Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs just has a hedging effectiveness of around 16%. From Table 20, I note that only the hedging effectiveness of Derivative-based ETFs is significantly different from those of the other three categories of ETFs, which means that using Derivative-based ETFs to hedge against crude oil price fluctuation is more effective than using other ETFs from the rest categories; on the other hand, the hedging performance of Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs is almost the same.

Table 19: In-sample comparison of Hedging Effectiveness based on MVaR

	MVaR_unhedged	MVaR_hedged	Hedging Effectiveness
Stock-based ETFs	0.0621	0.0496	20.06%
Derivative-based ETFs	0.0688	0.0324	47.54%
Derivative-based ETCs	0.0648	0.0547	15.63%
Single commodity ETFs	0.0702	0.0584	16.78%

Hedging Effectiveness: $HE^{MVaR} = \frac{MVaR_{unhedged} - MVaR_{hedged}}{MVaR_{unhedged}}$

Table 20: Comparison of hedging effectiveness based on the MVaR model for the different categories of ETFs: in-sample period

MVaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-2.4**	1.46	1
	(0.0268)	(0.1663)	(0.326)
Derivative-based ETFs		2.74**	3.99***
		(0.013)	(0.0004)
Derivative-based ETCs			-0.31
			(0.7592)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Table 21 and 22 show the results of out-of-sample hedging effectiveness and the results of the t-tests. As Table 20 indicates, the reduction in MVaR is more effective when using Derivative-based ETFs with reduction of MVaR of the hedged portfolio by 31.79%, which is consistent with the result from the in-sample period. The results of the t-tests show that the hedging effectiveness of Derivative-based ETFs is significantly different from those of the other categories, but it would not make much difference if we use Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs to hedge against crude oil price fluctuation.

Table 21: Out-of-sample comparison of Hedging Effectiveness based on MVaR

	MVaR_unhedged	MVaR_hedged	Hedging Effectiveness
Stock-based ETFs	419	0.0327	21.98%
Derivative-based ETFs	0.0420	0.0239	43.00%
Derivative-based ETCs	0.0420	0.0314	25.39%
Single commodity ETFs	0.0419	0.0323	22.94%

Hedging Effectiveness: $HE^{MVaR} = \frac{MVaR_{unhedged} - MVaR_{hedged}}{MVaR_{unhedged}}$

Table 22: Comparison of hedging effectiveness based on the MVaR model for the different categories of ETFs: out-of-sample period

MVaR	T-statistic		
	Derivative-based ETFs	Derivative-based ETCs	Single commodity ETFs
Stock-based ETFs	-2.11	-0.79	-0.22
	(0.0481)	(0.4432)	(0.8312)
Derivative-based ETFs		1.68	2.77
		(0.1095)	(0.0095)
Derivative-based ETCs			0.47
			(0.6438)

***indicates significance at the 99% confidence level;
** indicates significance at the 95% confidence level;
*indicates significance at the 99% confidence level.

Chapter VI. Conclusion and Discussion

This thesis investigates the hedging effectiveness of energy ETFs. I use 48 energy ETFs listed in US, Canada and London markets to examine whether they are effective in reducing the risk of crude oil price fluctuation. I categorize these ETFs into four categories based on their investment strategy and their top holdings (Table 1). I study the performance of the ETFs in the overall period starting from the inception date of each ETF till January 11, 2012. The overall period is split into the in-sample period and the out-of-sample period. The in-sample period covers the period from the inception date of each ETF till December 31, 2010 and is used to estimate optimal hedge ratios and in-sample hedging effectiveness. The out-of-sample period covers the period from January 1, 2011 till January 11, 2012 and is used to apply the optimal hedge ratios and calculate out-of-sample hedging effectiveness. The hedge ratios and measures of hedging effectiveness are based on: 1) the minimum variance hedge ratio (MVHR) model, which is applied by using two methods to estimate the optimal hedge ratios, an OLS regression and GARCH methodology; 2) models based on minimizing measures of risk based on value at risk (VaR), which are in turn, VaR, CVaR and MVaR.

The in-sample hedging effectiveness measures estimated by the five methods indicate that Derivative-based ETFs, which are traded in the US market and invest in derivatives such as futures and swaps, have the best hedging performance while there are no significant differences between the hedging performance of Stock-based ETFs, Derivative-based ETCs and Single-commodity ETFs. The poor performance of these ETFs could be due to several reasons. First, futures contracts are an effective way to hedge against oil price fluctuation but futures contracts are not accessible to small investors. Derivative-based ETFs may have some features of futures contracts since their asset allocation contains futures. The reason that Derivative-based ETFs outperform Derivative-based ETCs is probably due to differences in the regulation between the U.S. and U.K. markets. Since Stock-based ETFs just invest in the stocks of energy corporations, the price of these ETFs may not just be affected by crude oil prices but by other factors such as the company's own performance, which could affect the hedging effectiveness.

In the out-of-sample period, results from application of the VaR, CVaR and MVaR as measures of risk are consistent with those from the in-sample period. Hedging by Derivative-based ETFs is the most effective hedging instrument. Compared with the conventional hedging method OLS, hedging using a GARCH model, which takes into account time-varying variance, helps to reduce more risks. However, the downside of the bivariate GARCH model is the higher transaction cost caused by frequent rebalancing of the hedged portfolio.

In summary, energy ETFs, especially ones with investment in futures contracts, provide an effective way for small investors to hedge against crude oil price fluctuation. While, this thesis is limited to using energy ETFs to hedge against crude oil price fluctuation, in future research, the examination of hedging effectiveness can be extended to ETFs from other sectors such as real estate to hedge against the corresponding commodity price fluctuation. Also the hedging effectiveness of ETFs listed in different markets can be examined. Another extension could combine time-varying variances and covariances with the VaR or CVaR approach as recommended by Cao, Harris and Shen (2008).

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