Financial and Energy Exchange Traded Funds Futures: An evidence of Spillover and Portfolio Hedging

Abstract

This paper examines spillover from financial exchange traded funds (ETF) future to energy exchange traded funds (ETF) futures using adjusted daily data extending from April 2, 2009 to November 23, 2020. We also explore the portfolio hedging based conditional variance and co variance derived from dynamic conditional correlation. The proxies for the financial ETF futures are financial select sector SPDR fund (XLF) and generic 1st S&P 500 index futures (SP1) while generic 1st crude oil WTI futures (CL1), generic 1st natural gas futures (NG1) and energy select SPDR fund (XLE) are proxies of energy ETF future. The results obtained from Granger causality indicates that there is unidirectional causality from RXLF to RSP1 while bidirectional causality between RXLF and RCL1 at 5% significance level. Further, dynamic conditional correlation indicates the spillover effect from RXLF to RCL1, RXLF to RXLE, RSP1 to RCL1 and RSP1 to RXLE both in short run and long run. The spillover from RXLF to RNG1 is witnessed only in short run while the spillvoer from RSP1 to RNG1 is present in long run. The present study corroborates with the studies of Chang et al., (2018) and Lau et al., (2017). We notice that the average optimal hedge ratio of RXLF/RNG1 pair is most expensive while the cheapest hedging strategy is of RSP1/RCL1 pair.

Keywords: Financial ETF, Energy ETF, Spillover, Portfolio hedging, dynamic connectedness

1. Introduction

Exchange traded funds (ETF) is often referred to implied tradable spot price is actually spot index that facilitates trade and aims to provide the return mirroring that of an underlying benchmark index. ETF future is one of the derivative products based on existing exchange traded funds. It is an agreement or contract to buy or sell underlying ETF for a specified period of time and at an agreed-upon price. ETF futures act as a tool for investors for diversification of the non-systematic risk and reduction of total risk. It also allows for reduction in volatility as investment made into a bag of stocks or commodities rather than a single stock. ETFs are traded like stocks, while mutual funds trades happen on the end of the day prices. Moreover, due to passive management style the managing fees is found to be lower for ETFs as against mutual funds, making ETFs more popular with short-horizon liquidity traders (Ben-David et al., 2018). We thus chose ETFs against indices, mutual funds or derivatives of financial and energy markets as they fully represent the underlying indices and have a characteristic of being traded the spot as well as futures markets (Chang et al., 2017). Exchange Traded Funds (ETFs) were introduced in the financial markets in early 1990s and by 2020 assets under management globally amounted to approximately $7.74 trillion, of which United States accounted for more than 70 per cent of the global assets (approximately $5.6 trillion).

ETFs have been examined profusely to identify unidirectional price discovery and bidirectional volatility spillover (Krause and Tse, 2013) and portfolio optimization (Sawik, 2012). Furthermore, researchers examined the ETFs in various markets for examining spillover and volatility transmission, such as equity (Krause and Tse, 2013), oil (Aromi and Clements, 2017; Lau et al., 2017), energy (Tan et al., 2020), precious metals (Lau et al., 2017), agriculture (Chang et al., 2019).

The growing demand for energy is directly associated with the economic growth (Shahbaz et al., 2013) and has a measurable impact on energy and financial markets (Wang and Wang, 2019). The global financial crisis has caused an increase in the volatility in energy and financial markets (Tsuji, 2018). Volatility spillovers have been widely documented in energy futures market (Lin and Tamvakis, 2001) and its examination allows for preparing appropriate dynamic hedging strategy (Chang et al., 2018). Therefore, it becomes imperative to examine whether investors can benefit from inherent linkages between the financial sector and energy sector. Moreover, it would be interesting to examine how this relationship fans out in the spot and futures markets. The contributions of the present study are threefold: First, in spite of the limited associations in existing literatures, it contains broad proxies of financial ETF futures (financial select sector SPDR fund, Generic 1st S&P 500 index futures) and energy ETF futures (Generic 1st crude oil WTI futures, Generic 1st natural gas futures and energy select SPDR fund). Secondly, we do not consider only financial ETF future but also energy ETF future.

Thirdly, we include US ETF future for the analysis purpose based on dynamic conditional correlation, optimal portfolio weight and optimal hedge ratio.

To examine the spillover from financial sector to energy sector, we use the ETFs of both the sectors. Financial select sector SPDR fund (XLF) and Generic 1st S&P 500 index futures (SP1) were taken as proxies for financial sector. While, for representing the energy futures, three proxies have been employed, namely, Generic 1st crude oil WTI futures (CL1), Generic 1st natural gas futures (NG1) and energy select SPDR fund (XLE). By applying Granger Causality and Dynamic Conditional Correlation (DCC) GARCH, we seek to examine whether there is any spillover effect from financial ETF futures to Energy ETF futures. More importantly, we examine if such spillover will help derivatives market hedgers to minimise the risk and adopt appropriate hedging strategy by employing optimal portfolio weights and hedging ratio. The results of this study are expected to be of use to short-horizon liquidity traders who seek to exploit arbitrage opportunities by taking minimum risk. This study examines the ETFs of most important sectors and the findings would allow for determination of optimal portfolio with minimum risk.

The paper proceeds as follows. The next section presents the review of extant literature on the topic. Section 3 outlines the data used and econometric models employed in the study. Section 4 exhibits the results, and the final section draws out conclusions, important implications and scope for future research.

2. Literature Review

There are large number of evidences present in the literature on the use of exchange traded funds (ETFs) to measure the spill over effects on various markets, their performance in portfolio decisions, causality relationships between the volatility in various ETFs, etc. (Yavas and Rezayat, 2016; Ben-David et al., 2017; 2018; da Costa Neto et al., 2019). Most of these studies confirmed the significant role of ETFs to review the underlying index in portfolio decisions indicating the economic performance of the whole sector. da Costa Neto et al., (2019) explained the use of ETFs in various sectors including commodities, currencies, volatility, etc. that allow extensive exposure to traditional and exotic investment opportunities. They further confirmed that developed economies like US still prefer traditional ETFs investment strategies and in contrast, emerging markets like India and Brazil look for informational based arbitrage opportunities while investing in ETFs. In support to this, large studies confirmed ETFs as high volatile investment due to the increasing arbitrage opportunities and mispricing derived from ETFs and hence, preferred over individual's sectors, indices, stocks, etc. (Krause and Tse, 2013; Yavas and Rezayat, 2016; Chang et al., 2018). Poterba and Shoven (2002) mentioned exchange traded funds as one of the best investment avenues as it is found more tax efficient and holds more volatility in term of holding broad baskets of stocks. However, there are few portfolio studies that confirmed lack of information asymmetry in ETFs and low arbitrage opportunities in comparison to tradition stock portfolios (Chen, 2017). Keeping in mind the multiple views of the performance of ETFs in portfolio diversification, many studies draw their attention to measure the volatility spill over effect of ETFs in financial markets (Roy and Roy, 2017; Chang et al., 2019). The present study reviews the existing literature and applies the phenomenon in the US financial market to understand volatility spill over between energy and financial sector.

According to Krause et al., (2012), exchange traded funds have high volatility spill over effect due to its high liquidity and use of volatile derivatives used in respective ETFs. They also assessed the bidirectional spill over effect between ETFs futures and stocks and found higher effect from ETFs to stocks. In a later year, Krause and Tse (2013) indicated the volatility flow between two different equity market (Canadian and US) ETFs and confirmed the information diffusion to market participants. Such spill over effect in ETFs have been explored in different sectors in a single market (Chang et al., 2018), between two different equity markets (Marshall et al., 2013; Yavas and Rezayat, 2016), between two different sectors and markets (agriculture, commodities, equity, finance, etc. (Lau et al., 2017; Roy and Roy, 2017; Chang et al., 2019).

We also found few studies discussing the volatility correlation between energy and financial sectors and use of their respective ETFs for the investment decisions to streamline the current research (Lau et al., 2017; 2019).

Dependency of oil companies' performance on crude oil volatility, changing interest rates and bank loans are very high (McLannahan and Gray 2016; Ben-David et al., 2017). Studies confirmed that financial sector faces huge losses due to defaults and losses in oil companies' portfolios that lead to low credit deployment and poor interest margins to the financial sectors (Olson et al., 2016). Talking about developed economies like US, high volatility in oil prices affect the profit margins of energy and oil companies that may lead them to financial constraints including high price volatility, low credit ratings and poor market capitalizations (Zhu and Singh, 2016; Chang et al., 2017). In few decades, it has been noticed in US market that oil prices volatility has created uncertainty in revenues, cost to business to US oil companies and leads to huge defaults and loan crisis to energy and banking sector in the country (Krause et al., 2012; Zhu and Singh, 2016). Moreover, creation of synthetic oil by other markets like China and Brazil also creates price and profit fluctuations and leads to high volatility in US energy and banking sector (Diebold and Yilmaz, 2012; Ben-David et al., 2017). To conclude, consequences of such actions are very high and indicate low market performance to both the energy and financial sectors (Krause et al., 2012). Change (downfall) in stock prices and their respective ETFs data indicate such consequences and exhibit poor investment decisions with high risk (Diebold and Yilmaz, 2012; Ben-David et al., 2018). According to Chen and Huang (2010), such consequences and spill over effects should be assessed regularly by the fund managers and necessary actions including portfolio rebalancing, diversifications, etc. should be taken to get benefits of the situations. They further explained that due to high correlation between the performance of financial and energy sector, investors may include both (with same or opposite positions) for price discoveries, spill over effect, arbitration and hedging purposes.

In this regard, Gastineau (2002) indicated the strong volatility spill over effect between financial and energy sector ETFS and hence suitable for constructing a portfolio for hedging purpose. Baffles et al. (2015) found a strong correlation between oil prices and performance of financial (banking sector) across the globe. Chang et al., (2018) measured the strong volatility dissemination between energy and spot markets in US and UK market. Further to elaborate this context, Johnson and So (2012) found derivatives of ETFs in financial and energy sector more appropriate and liquid to exemplify the spill over effect of respective underlying sectors. Chang et al., (2017), mentioned futures of exchange traded funds are better than spot index for investments as they represent implied spot prices and have high tradability. In various related studies, it is confirmed that future and spot prices of ETFs may have an influence on another market prices of stocks or ETFs (Ben-David et al., 2016; da Costa et al., 2019).

To this end, the present study reviews the existing literature and proposes following objectives. First, the study assesses the volatility spill over effect between energy and financial sector ETFs derivatives in the US market. Understanding of ETFs price volatility in derivatives market may help firms, banks in price discovery and trade in future contracts influencing oil prices. Second, unlike existing literature with limited findings on spill over effect (Ben-David et al., 2016; Ben-David et al., 2017; da Costa et al., 2019), the study extends by measuring the portfolio weight and optimal hedge ratio between energy and financial US market. Very limited studies explored such data that highlights optimal hedging portfolios to banks, hedge funds, trading managers by using energy and financial ETFs derivatives (Elsayed et al. 2020. The present study fills the gap. Finally, the study used more than one proxy for each energy and financial ETFs future and tested various short term and long-term combinations of spill over effect between both the markets. This will help in portfolio designing and diversification strategies that are relevant to trader, finance managers, exporter and importers having exposure in both the markets in short and long run.

3. Data and Econometric Model

3.1 Data

The objective of this paper is to examine the spillover effect from financial ETF futures to energy ETF futures. The proxies for the financial ETF futures are financial select sector SPDR fund (XLF) and generic 1st S&P 500 index futures (SP1) while generic 1st crude oil WTI futures (CL1), generic 1st natural gas futures (NG1) and energy select SPDR fund (XLE) are proxies of energy ETF future. The daily adjusted closing price of the constituent series has been collected from April 2, 2009 to November 23, 2020. Further, the raw series has been converted into log return series by making logarithmic differences of two successive days prices. The following formula has been used to convert into log return series:

$$R_{i,t} = log\left(\frac{P_{i,t}}{(P_{i,t-1})}\right)$$

Where $R_{i,t}$ represents logarithmic return at time t, while $P_{i,t-1}$ and $P_{i,t}$ are the daily closing prices of ith fund on successive days. The table 1 furnishes data description of the considered series:

Market	Asset	Acronyms	Source
Financial ETF future	Financial select sector SPDR fund	XLF	Bloomberg
Financial ETF future	Generic 1st S&P 500 index futures	SP1	Bloomberg
Energy ETF future	Generic 1st crude oil WTI futures	CL1	Bloomberg
Energy ETF future	Generic 1st natural gas futures	NG1	Bloomberg
Energy ETF future	Energy select SPDR fund	XLE	Bloomberg

Source: Author's own presentation

3.2 Econometric Models

To examine the spillover effect, we apply econometric models like Granger causality and dynamic conditional correlation (DCC). Further, the portfolio weight and hedge ratio have been also calculated. This section describes the aforesaid models briefly:

3.2.1 Granger causality and dynamic conditional correlation

Granger causality is employed to examine the presence of causal linkages between two time series (Granger, 1969). The results allow to infer whether historical value of one series contains pertinent evidence to predict or influence change in other series (Friston et al., 2003). It also provides information on the direction of causality, whether it is unidirectional or bidirectional without any a priori hypothesis. Granger causality requires stationarity and if series are nonstationary, it is first converted to stationary series.

The literature on spillover presents evidence on use of various multivariate volatility models that examine conditional covariance. The notable among these are the diagonal model (Bollerslev et al..1988); diagonal vech model and multivariate GARCH model (Engle and Kroner, 1995); vector ARMA-GARCH or VARMA-GARCH model (Ling and McAleer, 2003); Dynamic Conditional Correlation (DCC) GARCH model (Eagle, 2002) and Varying

Conditional Correlation (VCC) model (Tse and Tsui, 2002). Based on perusal of these models and their prospective explanatory power, the DCC GARCH model of Eagle (2002) that assesses time varying correlations has been applied. Its estimation requires two steps, firstly the GARCH parameters are tested followed by estimation of correlations. To model r_{it}, the following equation is estimated:

$$r_{it} = a + b_1 r_{t-1} + \varepsilon_{it}, \quad \varepsilon_{it} = h_{it}^{(1/2)} v_{it}, \tag{1}$$

where a is constant, b_1 is the coefficient of lagged return, ε_{it} is the random error term that has conditional variance h_{it} while v_{it} is a vector n × 1 of residuals that are identically distributed and independent. In second step of DCC-GARCH, correlations are estimated using the following equation:

$$H_t = D_t R_t D_t \tag{2}$$

where H_t is a covariance matrix, R_t is a conditional covariance matrix *and* D_t is an n x n diagonal matrix with time varying standard deviations on the diagonal.

$$D_t = \text{diag}\,(h_{1t}^{1/2},\dots, h_{nt}^{1/2}) \tag{3}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

Where Qt is a symmetric positive definite matrix

$$Q_t = (1 - a - b)Q' + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{5}$$

Q' is an unconditional covariance matrix of the standardised errors and Qt^* is the diagonal matrix comprising of square root of diagonal of Qt which may be shown as diag ($q_{11t}^{1/2}$, $q_{22t}^{1/2}$,...,$q_{mnt}^{1/2}$). Two DCC parameters in the equation are a and b which are non-negative with a sum lower than 1. Lower conditional correlation is representative of higher diversification opportunities while higher values represent integration (Yu et al., 2010). The alpha and beta estimators derived from DCC-GARCH are time varying. Alpha measures the volatility impact for shorter duration while including the impact of persistence of residuals from preceding period. The beta in DCC measures the long-term impact of a shock on conditional correlation. The dynamic correlations are estimated as:

$$\rho_{ij,t} = q_{ij,t} \,/\, \sqrt{q_{ii,t}} \quad q_{jj,t} \tag{6}$$

Eagle (2002) estimates DCC GARCH model using two-step likelihood estimation method.

The likelihood function is presented as follows:

$$\left(L(\theta)\right) = -1/2 \sum_{t=1}^{T} \{ n \ln(2\pi) + 2\, lnln |D_t| + \ln(|R_t|) + \varepsilon_t{}' D_t^{-2} \varepsilon_t \tag{7}$$

So, this is a dynamic model with time-varying mean, variances and covariance.

3.2.2 Portfolio weight and hedging

Referring the results of dynamic conditional correlation, it is found that there is spillover from financial ETF future to energy ETF future. Therefore, it is important to check that how the financial ETF future risk or unfavourable financial ETF future movements can be hedged effectively. The major objective of this section is to furnish risk hedging strategy without reducing an expected return. Minimum variance hedge ratio is one of the popular hedging strategies which is based on portfolio variance minimization (Kroner & Sultan, 1993).

As per Kroner and Ng (1998), the optimal weight of financial ETF future in one-dollar portfolio of energy ETF future market in time t can be shown as below:

$$w^{ij,t} = \frac{h}{ii,t h - jj2h,t - ijh.t ij +, t hjj.t}$$

This portfolio is considered to have two different asset classes that is, i and *j*, where $w_{ij,t}$ is the weight assigned to asset 1 (financial ETF future), that is, *i* and (1-$w_{ij,t}$) was the weight of asset 2 (energy ETF future), that is j. $w_{ij,t}$ is the proportion of $1 investment made in portfolio of financial and energy ETF future. The time varying portfolio weight is computed applying the time varying conditional volatility and co-variances derived from the DCC model.

Finally, we analyse the diversification opportunities and respective hedge ratios of between financial ETF future and energy ETF future. To compute hedge ratio, Kroner and Sultan (1993) method is applied which is based on conditional co-variances and variances. The hedge ratio helps to hold long position in one asset that can be hedged with a short position in another asset to protect from the probable risk without reducing risk. The hedge ratio is shown as below:

$$\beta_{ijt} = h_{ijt}/h_{jjt}$$

where, β_{ijt} is the hedge ratio between asset 1, that is, *i* and asset 2, that is, *j*; h_{ijt} is the time varying conditional co-variances between *i* & *j* , h_{jjt} is the time varying conditional variances. The conditional variance and co-variance have been derived from DCC model.

4. Results and Discussion

This section includes the results obtained from summary statistics, Granger causality, dynamic conditional correlation, optimal portfolio weight and optimal hedge ratio.

4.1 Summary statistics and Granger Causality

To examine the spillover effect from financial exchange traded funds (ETF) futures to energy exchange traded funds (ETF) futures, we apply dynamic conditional correlation. Further, portfolio diversification opportunities have been identified using portfolio weight and hedge ratio. We initiate an analysis reporting the result of descriptive statistics which is presented in table 2. The mean of, RXLE, RSP1 and RCL1 is positive while NG1 reports negative mean which confirms that NG1 is riskier; the same has been witnessed by high standard deviation (0.0316) of this series. RXLF, RXLE and RSP1 exhibit negative skewness and RCL1 and RNG1 exhibit positive skewness. It ensures an asymmetric tail expanding towards more negative values. As per the kurtosis value, each series has leptokurtic distribution (greater than 3). It signifies that the financial ETF futures and energy ETF may generate either very large or very small future returns. Hence, the skewness and kurtosis imply the rejection of normality in these series which can be justified by the result of Jarque-Bera test. The Augmented – Dickey Fuller (ADF) and Phillips-Perron (PP) test have been applied to check the stationarity in these series. As per the results of ADF and PP test, it is confirmed that each series of financial ETF and energy ETF futures is stationary or integrated at level i.e. I (0). Figure 1 presents the time series plot of RXLF, RSP1, RXLE, RNG1 and RCL1. It is noticed that RXLF, RSP1, RXLE and RCL1 returns fell at the end of 2016 while RNG1 has realized the positive as well as negative stock return. This graphical representation helps us to understand how the series varied over the time. Every series is witnessed with volatility clustering as high changes are followed by high changes and low changes are followed by low changes in these series.

Further, Granger Causality test is applied to check the direction of transmission of information from financial ETF to energy ETF futures and vice-versa. Table 3 presents the result of Granger Causality. There is bidirectional causality between RXLF and RCL1 at 5% significance level. RXLF does not Granger cause RNG1 and vice versa. Similarly, RXLE does not Granger cause RCL1 and RNG1 while there is bidirectional causality between RXLE and RSP1. In sum, we observe that there is possibility of transmission of volatility from RXLF to RCL1 and from RXLE to RSP1 and vice versa while the study finds evidence of unidirectional transmission of information from RXLF to RSP1.

Table 2: Summary Statistics

	RXLF	RSP1	RCL1	RNG1	RXLE
Minimum	-0.1502	-0.1095	-0.2822	-0.1805	-0.2249
Maximum	0.1439	0.0935	0.3196	0.2677	0.1487
Mean	0.0005	0.0005	0.0003	-0.0001	0.0001
Std. dev	0.0171	0.0112	0.0246	0.0316	0.0170
Skewness	-0.0573	-0.6239	0.1684	0.7856	-0.8454
Kurtosis	10.9283	10.1094	27.7083	5.5860	16.2300
ARCH Test	0.0040	0.0000	0.0000	0.0000	0.0003
Jarque-Bera	20012	17384	126.39	5642.7	44609
Sig. value	0.0000	0.0000	0.0000	0.0000	0.0000
ADF Test	0.0000	0.0000	0.0000	0.0000	0.0003
PP Test	0.0010	0.0000	0.0000	0.0001	0.0000
Nobs	4016	4016	4016	4016	4016

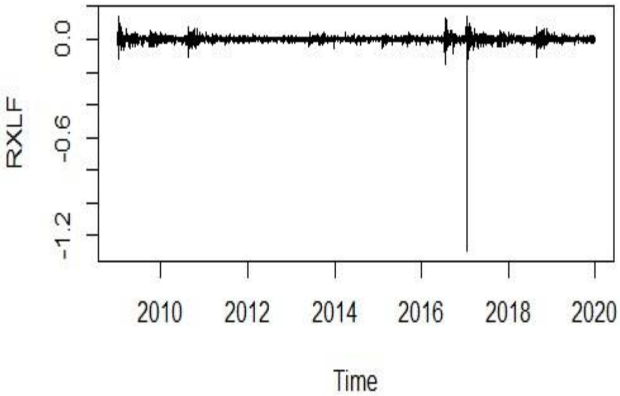
Source: Author’s own presentation

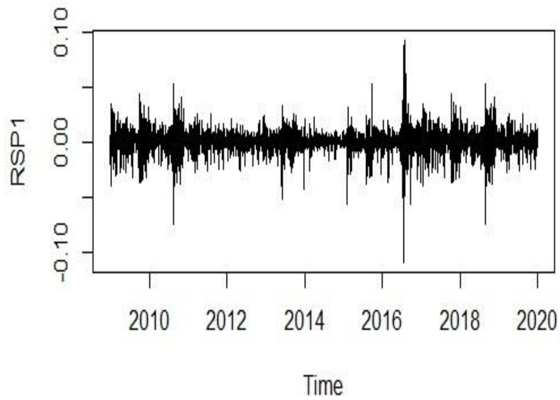
Table 3: Granger Causality Result

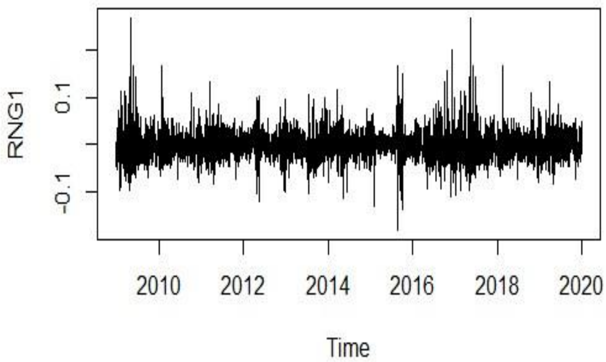
Null Hypothesis	F-value	Probability
RXLF does not Granger cause RCL1.	4.0013	0.04556 *
RCL1 does not Granger cause RXLF.	8.1868	0.03275 **
RXLF does not Granger cause RNG1.	4.0013	0.5156
RNG1 does not Granger cause RXLF.	1.1868	0.19540
RXLF does not Granger cause RXLE.	1.9605	0.16160
RXLE does not Granger cause RXLF.	0.0805	0.6916
RSP1 does not Granger cause RCL1.	1.6993	0.1005
RCL1 does not Granger cause RSP1.	0.4876	0.4851
RSP1 does not Granger cause RNG1.	2.8037	0.09416
RNG1 does not Granger cause RSP1.	0.034	0.8538
RSP1 does not Granger cause RXLE.	2.578	0.0313*
RXLE does not Granger cause RSP1.	3.1643	0.0132 *

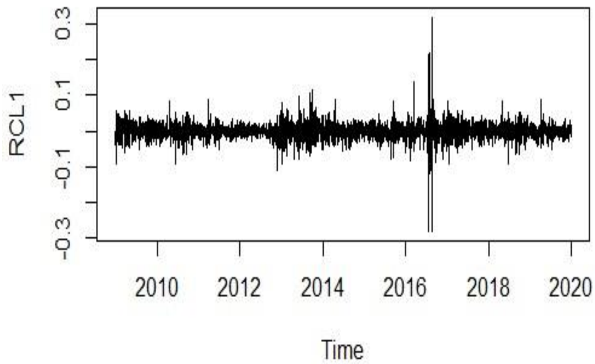
Source: Author's own presentation

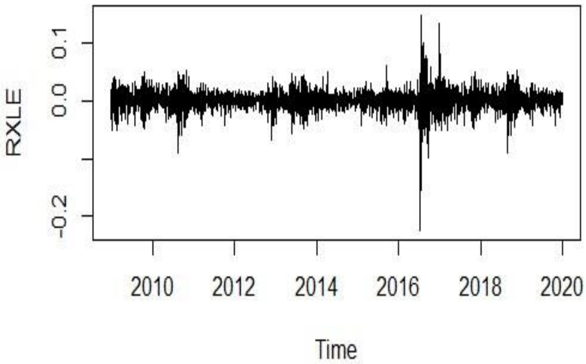
Figure 1: Time series plot of constituent series


RXLF
0.0
-0.6
-1.2
2010
2012
2014
2016
2018
2020
Time


RSP1
0.10
0.00
-0.10
2010
2012
2014
2016
2018
2020
Time


RNG1
0.1
-0.1
2010
2012
2014
2016
2018
2020
Time


RCL1
0.3
0.1
-0.1
-0.3
2010
2012
2014
2016
2018
2020
Time



4.2 Result of Dynamic conditional correlation

Next, we apply dynamic conditional correlation (DCC) GARCH to examine the spillover from financial exchange traded funds (ETF) futures to energy exchange traded funds (ETF) future.

we applied bivariate dynamic conditional correlation (DCC) GARCH presented in table 3. The table consists of spillover results from RXLF to RCL1, RXLF to RNG1, RXLF to RXLE, RSP1 to RCL1, RSP1 to RNG1 and RSP1 to RXLE. Referring the results of spillover from RXLF to RCL1, overall mean and constants are represented by “mu” and “omega”. “alpha 1” and “beta 1” signify the autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) respectively. The alpha shows whether there is volatility in short run or not which is based on the previous disturbances or error term. GARCH represents the persistence in the volatility that measures the impact of a shock on conditional correlation for the long run. Individually, the alpha1 and beta1 are positive and significant at 5% significance level which confirms the persistence of volatility. We observe that the sum of alpha1 and beta1 of both series is less than one which shows time decay over the time in volatility persistence. The sum of alpha and beta of RXLF and RCL1 are

0.9809 and 0.9882 respectively. It indicates that RXLF has fast decay in volatility persistence than RCL1. Further, dcca 1 and dccb 1 denotes the parameters of the dynamic conditional correlation. The coefficients of dcca 1 and dccb 1 are positive and significant at 5% significance level. It reveals that there is spillover or transmission of information in short run and long run. Turning to the spillover from RXLF to RNG1, we find the evidence of persistence in the volatility as alpha 1 and beta 1 of both series (RXLF and RNG1) are significant at 5% significant level. The sum of coefficients of alpha is less than 1 which confirms that there is time decay. Notably, RXLF is witnessed with fast time decay because the summation of coefficients of RXLF (0.9809) is less than the summation of coefficients of RNGI (0.9895).

The dcca1 parameter is positive and significant while the dccb1 is not significant. It ensures the evidence of short term long run spillover or transmission of information from RXLF to RNG1. It is worth noting that the summation of dcca1 and dccb1 is less than 1, therefore, dynamic conditional correlation is assumed to be mean reverting. As regards with DCC from RXLF to RXLE, the coefficients (alpha 1 and beta 1) of RXLF and RXLE are positive and significant. It indicates that there is short term and long-term persistence of the volatility. The sum of coefficients of both series is less than 1 which confirms the time decay in the series.

The dcca1 and dccb1 parameters are positive and significant, hence, we find the existence of short term and long term spillover from RXLF to RXLE.

Further, spillover from RSP1 to RCL1 has been checked. The alpha 1 and beta 1 of RSP1 and RCL1 are positive and significant. We find the evidence of short run and long run volatility persistence in both the series. The sum of their coefficients is 0.9814 and 0.9882 respectively, hence, there is fast decay of volatility persistence in RSP1 compared to RCL1. There is spillover or transmission of information of transmission from RSP1 to RCL1 as the dcca 1 and dccb 1 are positive and significant. Additionally, we examine spillover from RSP1 to NG1 and RSP1 to RXLE. The coefficients of each series are positive and significant, and their sum is less than one. The result confirms the short run and long run volatility persistence in each series.

Referring the spillover results from RSP1 to RNG1, we observe that the dcca 1 is positive but not significant which indicates that there is no spillover or no transmission of information in short run while there is existence of long run spillover as dccb 1 is positive an significant. At last, turning to the results of spillover from RSP1 to RXLE, we do not find spillover neither in short run nor in long run. The sum dcca 1 and dccb 1 is less than 1 which indicates that the dynamic conditional correlation is mean reverting.

Table 4: Results of pairwise DCC of constituent series

DCC from RXLF to RCL1				
	Estimate	Std. Error	t-statistics	P-value
[RXLF].mu	0.0008	0.0002	4.5922	0.0000
[RXLF].omega	0.0000	0.0000	0.7255	0.4681
[RXLF].alpha1	0.1424	0.0179	7.9665	0.0000
[RXLF].beta1	0.8385	0.0416	20.1358	0.0000
[RCL1].mu	0.0005	0.0002	2.4772	0.0132
[RCL1].omega	0.0000	0.0000	1.9282	0.0538
[RCL1].alpha1	0.0972	0.0192	5.0539	0.0000
[RCL1].beta1	0.8910	0.0193	46.2553	0.0000
[Joint]dcca1	0.0388	0.0039	9.9290	0.0000
[Joint]dccb1	0.9591	0.0042	226.9941	0.0000
DCC from RXLF to RNG1				
	Estimate	Std. Error	T-Statistics	P-value
[RXLF].mu	0.0008	0.0002	4.5898	0.0000
[RXLF].omega	0.0000	0.0000	0.7250	0.4685
[RXLF].alpha1	0.1424	0.0178	7.9887	0.0000

[RXLF].beta1	0.8385	0.0417	20.1066	0.0000
[RNG1].mu	0.0000	0.0004	-0.0055	0.9956
[RNG1].omega	0.0000	0.0000	1.0950	0.2735
[RNG1].alpha1	0.0740	0.0248	2.9859	0.0028
[RNG1].beta1	0.9155	0.0057	160.6857	0.0000
[Joint]dcca1	0.0375	0.0178	2.1002	0.0357

[Joint]dccb1	0.4780	0.2898	1.6498	0.0990
DCC from RXLF to RXLE				
[RXLF].mu	0.0008	0.0002	4.5922	0.0000
[RXLF].omega	0.0000	0.0000	0.7255	0.4681
[RXLF].alpha1	0.1424	0.0179	7.9665	0.0000
[RXLF].beta1	0.8385	0.0416	20.1358	0.0000
[RXLE].mu	0.0005	0.0002	2.4772	0.0132
[CL1].omega	0.0000	0.0000	1.9282	0.0538
[RXLE].alpha1	0.0972	0.0192	5.0539	0.0000
[RXLE].beta1	0.8910	0.0193	46.2553	0.0000
[Joint]dcca1	0.0388	0.0039	9.9290	0.0000
[Joint]dccb1	0.9591	0.0042	226.9941	0.0000
DCC from RSP1 to CL1				
[sp1].mu	0.0008	0.0001	6.1684	0.0000
[sp1].omega	0.0000	0.0000	1.0793	0.2805
[sp1].alpha1	0.1769	0.0197	8.9983	0.0000
[sp1].beta1	0.8045	0.0243	33.1224	0.0000
[CL1].mu	0.0005	0.0002	2.4792	0.0132
[CL1].omega	0.0000	0.0000	1.9216	0.0547
[CL1].alpha1	0.0972	0.0193	5.0461	0.0000
[CL1].beta1	0.8910	0.0193	46.1105	0.0000
[Joint]dcca1	0.0448	0.0049	9.0526	0.0000
[Joint]dccb1	0.9540	0.0051	186.1126	0.0000
DCC from RSP1 to NG1				
[RSP1].mu	0.0008	0.0001	6.1629	0.0000
[RSP1].omega	0.0000	0.0000	1.0856	0.2776
[RSP1].alpha1	0.1769	0.0197	8.9940	0.0000
[RSP1].beta1	0.8045	0.0239	33.6584	0.0000
[RNG1].mu	0.0000	0.0004	-0.0055	0.9956
[RNG1].omega	0.0000	0.0000	1.0952	0.2734
[RNG1].alpha1	0.0740	0.0248	2.9862	0.0028
[RNG1].beta1	0.9155	0.0057	160.8183	0.0000
[Joint]dcca1	0.0028	0.0037	0.7686	0.4422
[Joint]dccb1	0.9841	0.0258	38.1849	0.0000
DCC from RSP1 to RXLE				

[RSP1].mu	0.0000	0.0004	-0.0055	0.9956
[RSP1].omega	0.0000	0.0000	1.0947	0.2737
[RSP1].alpha1	0.0740	0.0248	2.9844	0.0028
[RSP1].beta1	0.9155	0.0057	160.8932	0.0000
[RXLE].mu	0.0005	0.0002	2.4789	0.0132
[CL1].omega	0.0000	0.0000	1.9270	0.0540
[RXLE].alpha1	0.0972	0.0192	5.0539	0.0000

[RXLE].beta1	0.8910	0.0193	46.2229	0.0000
[Joint]dcca1	0.0073	0.0026	2.8352	0.0046
[Joint]dccb1	0.9881	0.0048	207.1377	0.0000

Source: Author's own presentation

4.3 Portfolio weight and hedge ratio

After investigating the spillover from financial exchange traded funds (ETF) futures to energy exchange traded funds (ETF) futures, portfolio weight and hedging ratio are calculated considering the series of conditional variance and conditional covariance derived from symmetrical DCC-GARCH. Creating an optimal portfolio by managing the risk needs temporal covariance matrix. We calculate optimal portfolio weights to mitigate the risk efficiently in financial ETF future and energy ETF future. In addition, we compute hedge ratios to design the strategy of optimal hedging. To reduce the risks without decreasing expected returns, we can build a portfolio of financial ETF future and energy ETF future. We present that a portfolio investor hedges the exposure to financial ETF future movements by investing their funds in energy ETF futures. For the portfolio weight and hedging, we apply Kroner and Ng (1998) and Kroner and Sultan (1993) respectively. The mean of portfolio weight indicates the optimal allocation of financial ETF futures to energy ETF futures to reduce the portfolio risk without changing expected returns. Further, the mean of hedge ratio shows that investors can take either a short or long position for the constituent series. Table 5 presents the summary of portfolio weights and hedge ratio of financial ETF futures (RXLF, RSP1) and energy ETF futures (RCL1, RNG1 and RXLE). Referring the results of summary of portfolio weights presented in table 5, it ranges from 0.024 to 0.232 which are assigned to the SP1/NG1 and SP1/XLE respectively; lowest weight 0.024 signifies that for a portfolio of $1, 2 cents has to be invested in SP1 and remainder 98 (1-W_{jit}) cents must be invested in NG1. Comparatively, high weights (0.232) indicates that 23 cents must be invested in SP1 and rest of the 77 cents (1-W_{jit}) should be invested in XLE.

Table 5: Summary statistics of portfolio weight and hedge ratio

Portfolio Weights				
Series	**Mean**	**Std. Dev**	**Min**	**Max**
RXLF/RCL1	0.1684	0.2001	-0.3976	0.6341
RXLF/RNG1	0.0318	0.0372	-0.1635	0.2569
RXLF/RXLE	0.2156	0.3440	-0.2953	0.8844
RSP1/RCL1	0.1684	0.2002	-0.3975	0.6343
RSP1/RNG1	0.0244	0.0079	0.0062	0.0478
RSP1/RXLE	0.2320	0.3697	-0.3365	0.935
Hedge Ratio				
Series	Mean	St Dev	Min	Max
RXLF/RCL1	0.0373	0.0701	0.0070	1.0488
RXLF/RNG1	0.0428	0.0352	0.0115	0.34563
RXLF/RXLE	0.0268	0.0540	0.0048	0.8132
RSP1/RCL1	0.0133	0.0196	-1.010	19.4078
RSP1/RNG1	0.0303	0.0246	0.0077	0.3160
RSP1/RXLE	0.0191	0.0400	0.0027	0.6636

Source: Author's own presentation

Further, we compute the hedge ratio proposed by Kroner and Sultan (1993) to mitigate the risk of the portfolio (financial ETF future and energy ETF future) presented in table 5. We consider by how much a long position of $1 in financial ETF future can be hedged by a short position in energy ETF future. Long position signifies "buy" whereas short position indicates "sell". We observe that the average optimal hedge ratio of RXLF/RNG1 pair (0.0428) is most expensive while the cheapest hedging strategy is of RSP1/RCL1 pair (0.0133). The optimal hedge ratio of RXLF/RNG1 signifies that $1 long position in financial ETF futures should be hedged shorting an investment of energy ETF future by 4 cents to minimize the risk. Similarly, the hedge ratio of RSP1/RCL1 shows that the volatility in the portfolio can be hedged holding $1 long position in RSP1 by 1 cent investment in RCL1. To be precise, the hedging costs of the RXLF investments undertaking the short position in RNG1 is high than rest of the pairs. The present study corroborates with the studies of Chang et al., (2018) and Lau et al., (2017).

5. Conclusion and policy implications

Exchange traded fund (ETF) is considered as one of the tradable assets that tracks an index reflecting the economic condition of underlying sector. It has potential catalyst to furnish systematic reduction of risk for the portfolio and preferred more by short-horizon liquidity traders. The popularity of the financial ETF future has grown with an increase of adoption of standard ETF. On the other hand, due to the rapid development and huge demand of energy products, investors prefer the energy ETF future. Derivative market hedgers, further, want to minimize the risk adopting an appropriate hedging strategy with optimal portfolio weight and hedge ratio. This paper investigates the spillover effect from financial ETF to energy ETF and build optimal portfolio weight and hedge ratio to minimize the risk.

We employ Granger causality and dynamic conditional correlation using daily data extending from April 2, 2009 to November 23, 2020. The results obtained from Granger causality indicates that there is unidirectional causality from RXLF to RSP1 while bidirectional causality between RXLF and RCL1 at 5% significance level. Rest of the variables do not have cause and effect relationship. Further, dynamic conditional correlation indicates the spillover effect from RXLF to RCL1, RXLF to RXLE, RSP1 to RCL1 and RSP1 to RXLE both in short run and long run. The spillover from RXLF to RNG1 is witnessed only in short run while the spillvoer from RSP1 to RNG1 is present in long run. The present study corroborates with the studies of Chang et al., (2018) and Lau et al., (2017). After investigating the spillover from financial exchange traded funds (ETF) futures to energy exchange traded funds (ETF) futures, portfolio weight and hedging ratio are calculated to minimize the risk for ETF investor without reducing expected return. The portfolio weight ranges from 0.024 to 0.232 which are assigned to the SP1/NG1 and SP1/XLE respectively. Referring the result of optimal hedge ratio proposed by by Kroner and Sultan (1993), we notice that the average optimal hedge ratio of RXLF/RNG1 pair (0.0428) is most expensive while the cheapest hedging strategy is of RSP1/RCL1 pair (0.0133).

The contributions of the present study are threefold: First, in spite of the limited associations in existing literatures, it contains broad proxies of financial ETF futures (financial select sector SPDR fund, Generic 1st S&P 500 index futures) and energy ETF futures (Generic 1st crude oil WTI futures, Generic 1st natural gas futures and energy select SPDR fund). Secondly, we do not consider only financial ETF future but also energy ETF future. Thirdly, we include US ETF future for the analysis purpose based on dynamic conditional correlation, optimal portfolio weight and optimal hedge ratio. It has two policy implications. First, our result indicates the spillover or dynamic connectedness from financial ETF future to energy ETF future. The ETF exchange must know this fact and monitor the pricing accordingly with respect to the demand and supply gap in exchange traded fund (ETF) market. Second, it furnishes the hedging across the ETF tradeable asset due to which an investor knows how much they should invest in financial ETF future and energy ETF future. Apart from investor, regulators and policymakers must be aware of dynamic linkages and spillover of the volatility among constituent variables.

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Financial and Energy Exchange Traded Funds Futures: An evidence of Spillover and Portfolio Hedging

Abstract

This paper examines spillover from financial exchange-traded funds (ETF) futures to energy ETF futures using adjusted daily data extending from April 2, 2009, to November 23, 2020. We also explore the portfolio hedging-based conditional variance and co-variance derived from dynamic conditional correlation. The proxies for the financial ETF futures are financial select sector SPDR fund (XLF) and generic 1st S&P 500 index futures (SP1) while generic 1st crude oil WTI futures (CL1), generic 1st natural gas futures (NG1), and energy select SPDR fund (XLE) are proxies of energy ETF futures. The results obtained from Granger causality indicate that there is unidirectional causality from RXLF to RSP1 while bidirectional causality between RXLF and RCL1 at a 5% significance level. Further, dynamic conditional correlation indicates the spillover effect from RXLF to RCL1, RXLF to RXLE, RSP1 to RCL1, and RSP1 to RXLE both in the short-run and long run. The spillover from RXLF to RNG1 is witnessed only in the short run while the spillover from RSP1 to RNG1 is present in long run. The present study corroborates with the studies of Chang et al., (2018) and Lau et al., (2017). We notice that the average optimal hedge ratio of the RXLF/RNG1 pair is the most expensive while the cheapest hedging strategy is of RSP1/RCL1 pair.

Keywords: Financial ETF, Energy ETF, Spillover, Portfolio hedging, dynamic connectedness

1. Introduction

An Exchange traded fund (ETF) is often referred to as implied tradable spot price which is a spot index that facilitates trade and aims to provide the return mirroring that of an underlying benchmark index. ETF futures is one of the derivative products based on existing exchange traded funds. It is an agreement or contract to buy or sell underlying ETF for a specified period and at an agreed-upon price. ETFs and ETF futures act as tools for investors for diversification of the non-systematic risk and reduction of total risk. They also allow for a reduction in volatility as an investment is made into a bag of stocks or commodities rather than a single stock. Both mutual funds and ETFs allow for diversification however, they are fundamentally different as ETFs are traded like stocks, while mutual funds trades happen on the end of the day prices. Moreover, due to the passive management style, the managing fees are found to be lower for ETFs as against mutual funds, making ETFs more popular with short-horizon liquidity traders (Ben-David et al., 2018). We thus chose ETFs against indices, mutual funds, or derivatives of financial and energy markets as they fully represent the underlying indices and have a characteristic of being traded on the spot as well as futures markets (Chang et al., 2017).

ETFs were introduced in the financial markets in the early 1990s and by 2020 assets under management globally amounted to approximately $7.74 trillion, of which the United States accounted for more than 70 percent of the global assets (approximately $5.6 trillion).

ETFs have been examined profusely to identify unidirectional price discovery and bidirectional volatility spillover (Krause and Tse, 2013), and portfolio optimization (Sawik, 2012). Furthermore, researchers examined the ETFs in various markets for examining spillover and volatility transmission, such as equity (Krause and Tse, 2013), oil (Aromi and Clements, 2017; Lau et al., 2017), energy (Tan et al., 2020), precious metals (Lau et al., 2017), agriculture (Chang et al., 2019).

The growing energy demand is directly associated with economic growth (Shahbaz et al., 2013; Yadav et a.., 2020) and has a measurable impact on energy and financial markets (Wang and Wang, 2019). The global financial crisis has caused an increase in volatility in energy and financial markets (Tsuji, 2018). Volatility spillovers have been widely documented in the energy futures market (Lin and Tamvakis, 2001) and its examination allows for preparing an appropriate dynamic hedging strategy (Chang et al., 2018). Therefore, it becomes imperative to examine whether market participants can benefit from inherent linkages between the financial sector and the energy sector. Moreover, it would be interesting to examine how this relationship pans out in the futures markets.

This study is relevant and contributes to the existing body of knowledge in following ways.

First, the study assesses the volatility spillover effect between energy and financial sector ETFs derivatives in the US market. Understanding ETFs price volatility in the derivatives market may help firms, banks in price discovery and trade in futures contracts influencing oil prices. Financial select sector SPDR fund (XLF) and Generic 1st S&P 500 index futures (SP1) are taken as proxies for the financial sector. While, for representing the energy futures, three proxies have been employed, namely, Generic 1st crude oil WTI futures (CL1), Generic 1st natural gas futures (NG1), and energy select SPDR fund (XLE). Second, the study extends the limited findings on the spillover effect (Ben-David et al., 2016; Ben-David et al., 2017; da Costa et al., 2019), by measuring the portfolio weight and optimal hedge ratio between energy and financial US market. Very limited studies explored such data that highlights optimal hedging portfolios to banks, hedge funds, trading managers by using energy and financial ETFs derivatives (Elsayed et al. 2020). The present study fills the gap. Finally, the study uses more than one proxy for each energy and financial ETFs futures and tested various short-term and long-term combinations of spillover effects between both the markets. The findings of this study will help in portfolio designing and diversification strategies that are relevant to the traders, finance managers, exporters, and importers having exposure in both the markets in the short and long run. Explicitly, the results of this study are expected to be of use to short-horizon liquidity traders who seek to exploit arbitrage opportunities by taking the minimum risk. It would also be beneficial for derivatives market hedgers to minimize the risk and adopt an appropriate hedging strategy by employing optimal portfolio weights and hedging ratios.

The paper proceeds as follows. The next section presents the review of the extant literature on the topic. Section 3 outlines the data used and econometric models employed in the study. Section 4 exhibits the results, and the final section draws out conclusions, important implications and scope for future research.

2. Literature Review

Extant literature documents the use of ETFs to measure the spillover effects on various markets, assess performance in portfolio decisions, causality relationships between the volatility in various ETFs, etc. (Yavas and Rezayat, 2016; Ben-David et al., 2017; 2018; da Costa Neto et al., 2019). Most of these studies confirmed the significant role of ETFs to review the role of the underlying index in portfolio decisions indicating the economic performance of the whole sector. da Costa Neto et al., (2019) explained the use of ETFs in various sectors including commodities, currencies, volatility, etc. that allow extensive exposure to traditional and exotic investment opportunities. They further confirmed that developed economies like the US still prefer traditional ETFs investment strategies and in contrast, emerging markets like India and Brazil look for informational-based arbitrage opportunities while investing in ETFs. In support of this, a large number of studies confirmed ETFs as a highly volatile investment option due to the increasing arbitrage opportunities and mispricing derived from ETFs and hence, preferred over individual's sectors, indices, stocks, etc. (Krause and Tse, 2013; Yavas and Rezayat, 2016; Chang et al., 2018).

Poterba and Shoven (2002) mentioned exchange traded funds (ETFs) as one of the best investment avenues as it is found more tax-efficient and holds more volatility in terms of holding broad baskets of stocks. However, few portfolio studies confirmed the lack of information asymmetry in ETFs and low arbitrage opportunities in comparison to traditional stock portfolios (Chen, 2017). Keeping in mind the multiple views of the performance of ETFs in portfolio diversification, many studies draw their attention to measuring the volatility spillover effect of ETFs in financial markets (Roy and Roy, 2017; Chang et al., 2019). According to Krause et al., (2012), exchange traded funds have high volatility spillover effect due to their high liquidity and use of volatile derivatives used in respective ETFs. They also assessed the bidirectional spillover effect between ETFs futures and stocks and found higher effects from ETFs to stocks. Later, Krause and Tse (2013) indicated the volatility flow between two different equity market (Canadian and US) ETFs and confirmed the information diffusion to market participants. Such spillover effects in ETFs have been explored in different sectors in a single market (Chang et al., 2018), between two different equity markets (Marshall et al., 2013; Yavas and Rezayat, 2016), between two different sectors and markets (agriculture, commodities, equity, finance, etc. (Lau et al., 2017; Roy and Roy, 2017; Chang et al., 2019).

We found few studies discussing the volatility correlation between energy and financial sectors and the use of their respective ETFs for the investment decisions to streamline the current research (Lau et al., 2017; 2019). In this context, few studies explained that the dependency of oil companies' performance on crude oil volatility, changing interest rates, and bank loans are very high (McLannahan and Gray 2016; Ben-David et al., 2017). Studies confirmed that the financial sector faces huge losses due to defaults and losses in oil companies' portfolios that lead to low credit deployment and poor interest margins to the financial sectors (Olson et al., 2016). Talking about developed economies like the US, high volatility in oil prices affects the profit margins of energy and oil companies that may lead them to financial constraints including high price volatility, low credit ratings, and poor market capitalizations (Zhu and Singh, 2016; Chang et al., 2017). In the last few decades, it has been noticed in the US market that oil prices volatility has created uncertainty in revenues, cost to business to US oil companies and leads to huge defaults and loan crises to energy and banking sector in the country (Krause et al., 2012; Zhu and Singh, 2016). Moreover, the creation of synthetic oil by other markets like China and Brazil also creates price and profit fluctuations and leads to high volatility in the US energy and banking sector (Diebold and Yilmaz, 2012; Ben-David et al., 2017). To conclude, the consequences of such actions are very high and indicate low market performance to both the energy and financial sectors (Krause et al., 2012). Change (downfall) in stock prices and their respective ETFs data indicate such consequences and exhibit poor investment decisions with high risk (Diebold and Yilmaz, 2012; Ben-David et al., 2018). According to Chen and Huang (2010), such consequences and spillover effects should be assessed regularly by the fund managers and necessary actions including portfolio rebalancing, diversifications, etc. should be taken to get benefits of the situations. They further explained that due to the high correlation between the performance of the financial and energy sectors, investors may include both (with the same or opposite positions) for price discoveries, spillover effect, arbitration, and hedging purposes.

In this regard, Gastineau (2002) indicated the strong mean return spillover effect between financial and energy sector ETFs and hence suitable for constructing a portfolio for hedging purposes. Baffles et al. (2015) found a strong correlation between oil prices and the performance of the financial (banking sector) across the globe. Chang et al., (2018) measured the strong mean-volatility dissemination between energy and spot markets in US and UK markets. Further to elaborate this context, Johnson and So (2012) found derivatives of ETFs in the financial and energy sectors more appropriate and liquid to exemplify the spillover effect of respective underlying sectors. Chang et al., (2017), mentioned futures of exchange traded funds are better than spot index for investments as they represent implied spot prices and have high tradability. In various related studies, it is confirmed that future and spot prices of ETFs may influence other market prices of stocks or ETFs (Ben-David et al., 2016; da Costa et al., 2019). The present study is in line with the findings of Chang et al. (2018). Unlike Chang et al., (2018) findings that explained the volatility spillover effect between financial and energy sector ETFs in both spot and futures markets, the present study discussed the spillover effect only in the futures market. Second, the present study not only measures the volatility spillover effect between financial and energy ETFs in the US market like Chang et al. (2018) but also takes a step further by suggesting portfolio risk hedging strategies with calculating optimal hedge ratio and portfolio weights.

The present study reviews the existing literature and finds the following research gaps in the literature: First, with regards to volatility spillover effects among various sectors, most studies focussed mainly on energy markets, commodity markets, and foreign exchange markets or spillover effect among developed and developing countries ETFs particularly, equity ETFs. We still lack studies measuring the spillover effect between ETFs of energy and the financial sector in the US context. Second, the majority of past studies used one or two benchmarks for testing the spillover effect. The present study includes six diversified ETFs from the financial sector, energy sector, an index fund, and two ETFs futures on crude oil, natural gas to broaden the scope of present findings. Moreover, the study measures the dynamic correlation along with unidirectional and bidirectional causality among all the funds. Third, methodologically, most past studies tested the short-term or long-term movement or co-movement between the ETFs in these markets. In addition, those studies mainly focused on mean return spillover with less focus on risk spillover effects. The present study fills the gap by measuring both short- and long-term volatility or risk spillover effect between energy and financial ETFs in US financial market. Fourth, the present study used daily data as opposed to weekly or monthly data used in the literature. Daily data provides a larger set of observations that may help select hedge funds and develop portfolio hedging strategies. Also, ETFs are recently available and not very old traded funds, so daily data is better for the observations. Finally, and most importantly, the study extends the literature by not only measuring the spillover effect but suggesting portfolio risk hedging strategies through portfolio weights distributed among the benchmark ETFs and with the help of optimal hedge ratio.

3. Data and Econometric Model

3.1 Data

The objective of this paper is to examine the spillover effect from financial ETF futures to energy ETF futures. The proxies for the financial ETF futures are financial select sector SPDR fund (XLF) and generic 1st S&P 500 index futures (SP1) while generic 1st crude oil WTI futures (CL1), generic 1st natural gas futures (NG1), and energy select SPDR fund (XLE) are proxies of energy ETF futures. The daily adjusted closing price of the constituent series has been collected from April 2, 2009, to November 23, 2020. Further, the raw series has been converted into log return series by making logarithmic differences of two successive days prices. The following formula has been used to convert into log return series:

$$R_{i,t} = log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

Where $R_{i,t}$ represents logarithmic return at time t, while $P_{i,t-1}$ and $P_{i,t}$ are the daily closing prices of the ith fund on successive days. Table 1 furnishes data description of the considered series.

Table 1: Data Description

Market	Asset	Acronyms	Source
Financial ETF futures	Financial select sector SPDR fund	XLF	Bloomberg
Financial ETF futures	Generic 1st S&P 500 index futures	SP1	Bloomberg
Energy ETF futures	Generic 1st crude oil WTI futures	CL1	Bloomberg
Energy ETF futures	Generic 1st natural gas futures	NG1	Bloomberg
Energy ETF futures	Energy select SPDR fund	XLE	Bloomberg

Source: Author's own presentation

3.2 Econometric Models

To examine the spillover effect, we apply econometric models like Granger causality and dynamic conditional correlation (DCC). Further, the portfolio weight and hedge ratio have been also calculated. This section describes the aforesaid models briefly:

3.2.1 Granger causality and dynamic conditional correlation

Granger causality is employed to examine the presence of causal linkages between two time series (Granger, 1969). The results allow inferring whether the historical value of one series contains pertinent evidence to predict or influence change in other series (Friston et al., 2003). It also provides information on the direction of causality, whether it is unidirectional or bidirectional without any a priori hypothesis. Granger causality requires stationarity and if series are nonstationary, it is first converted to stationary series.

The literature on spillover presents evidence on the use of various multivariate volatility models that examine conditional covariance. The notable among these are the diagonal model (Bollerslev et al.,1988); diagonal vech model and multivariate GARCH model (Engle and Kroner, 1995); vector ARMA-GARCH or VARMA-GARCH model (Ling and McAleer, 2003); Dynamic Conditional Correlation (DCC) GARCH model (Eagle, 2002) and Varying Conditional Correlation (VCC) model (Tse and Tsui, 2002). Based on a perusal of these models and their prospective explanatory power, the DCC GARCH model of Eagle (2002) that assesses time-varying correlations has been applied. Its estimation requires two steps, firstly the GARCH parameters are tested followed by estimation of correlations. To model r_{it}, the following equation is estimated:

$$r_{it} = a + b_1 r_{t-1} + \varepsilon_{it}, \quad \varepsilon_{it} = h_{it}^{(1/2)} v_{it}, \tag{2}$$

where a is constant, b_1 is the coefficient of lagged return, ε_{it} is the random error term that has conditional variance h_{it} while v_{it} is a vector n × 1 of residuals that are identically distributed and independent. In second step of DCC-GARCH, correlations are estimated using the following equation:

$$H_t = D_t R_t D_t \tag{3}$$

where H_t is a covariance matrix, R_t is a conditional covariance matrix *and* D_t is an n x n diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = \text{diag}\,(h_{1t}^{1/2}, ..., h_{nt}^{1/2}) \tag{4}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

Where Q_t is a symmetric positive definite matrix

$$Q_t = (1 - a - b)Q' + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{6}$$

Q' is an unconditional covariance matrix of the standardized errors and Q_t^* is the diagonal matrix comprising of the square root of diagonal of Q_t which may be shown as diag ($q_{11t}^{1/2}$, $q_{22t}^{1/2}$,...,$q_{mnt}^{1/2}$). Two DCC parameters in the equation are a and b which are non-negative with a sum lower than 1. Lower conditional correlation is representative of higher diversification opportunities while higher values represent integration (Yu et al., 2010). The alpha and beta estimators derived from DCC-GARCH are time-varying. Alpha measures the volatility impact for a shorter duration while including the impact of persistence of residuals from the preceding period. The beta in DCC measures the long-term impact of a shock on conditional correlation. The dynamic correlations are estimated as:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}} \qquad (7)$$

Eagle (2002) estimates DCC GARCH model using the two-step likelihood estimation method. The likelihood function is presented as follows:

$$ln\big(L(\theta)\big) = -1/2 \sum_{t=1}^{T} \{n \ln(2\pi) + ln\ |D_t|^2 + \ln(|R_t|) + \varepsilon_t{}' D_t^{-2}\ \varepsilon_t \qquad (8)$$

So, this is a dynamic model with time-varying mean, variances, and covariance.

3.2.2 Portfolio weight and hedging

Referring to the results of dynamic conditional correlation, it is found that there is spillover from financial ETF futures to energy ETF futures. Therefore, it is important to check that how the financial ETF futures risk or unfavorable financial ETF futures movements can be hedged effectively. The major objective of this section is to furnish a risk hedging strategy without reducing an expected return. The minimum variance hedge ratio is one of the popular hedging strategies which is based on portfolio variance minimization (Kroner & Sultan, 1993).

As per Kroner and Ng (1998), the optimal weight of financial ETF futures in the one-dollar portfolio of energy ETF future market in time t can be shown as below:

$$\boldsymbol{Wij,t} = \boldsymbol{h}\underline{\hspace{4cm}}\boldsymbol{ii,th-jj2h,t-ijh.tij+,thjj.t}$$

(9)

This portfolio is considered to have two different asset classes that is, i and j, where $\boldsymbol{w_{ij,t}}$ is the weight assigned to asset 1 (financial ETF futures), that is, i and (1-$\boldsymbol{w_{ij,t}}$) was the weight of asset 2 (energy ETF futures), that is j. $\boldsymbol{w_{ij,t}}$ is the proportion of \$1 investment made in the portfolio of financial and energy ETF futures. The time-varying portfolio weight is computed applying the time-varying conditional volatility and co-variances derived from the DCC model.

Finally, we analyze the diversification opportunities and respective hedge ratios between financial ETF futures and energy ETF futures. To compute hedge ratio, Kroner and Sultan (1993) method is applied which is based on conditional co-variances and variances. The hedge ratio helps to hold a long position in one asset that can be hedged with a short position in another asset to protect from the probable risk without reducing risk. The hedge ratio is shown as below:

$$\beta_{ijt} = h_{ijt}/h_{jjt} \tag{10}$$

where, β_{ijt} is the hedge ratio between asset 1, that is, i and asset 2, that is, j; h_{ijt} is the time-varying conditional co-variances between i & j , h_{jjt} is the time-varying conditional variances. The conditional variance and co-variance have been derived from DCC model.

4. Results and Discussion

This section includes the results obtained from summary statistics, Granger causality, dynamic conditional correlation, optimal portfolio weight, and optimal hedge ratio.

4.1 Summary statistics and Granger Causality

To examine the spillover effect from financial ETF futures to energy ETF futures, we applied dynamic conditional correlation. Further, portfolio diversification opportunities have been identified using portfolio weight and hedge ratio. We initiate an analysis reporting the result of descriptive statistics which is presented in table 2. The mean of, RXLE, RSP1 and RCL1 is positive while NG1 reports a negative mean which confirms that NG1 is riskier; the same has been witnessed by the high standard deviation (0.0316) of this series. RXLF, RXLE and RSP1 exhibit negative skewness, and RCL1 and RNG1 exhibit positive skewness. It ensures an asymmetric tail expanding towards more negative values. As per the kurtosis value, each series has leptokurtic distribution (greater than 3). It signifies that the financial ETF futures and energy ETF may generate either very large or very small impending returns. Hence, the skewness and kurtosis imply the rejection of normality in these series which can be justified by the result of Jarque-Bera test. The Augmented – Dickey Fuller (ADF) and Phillips-Perron (PP) test have been applied to check the stationarity in these series. As per the results of ADF and PP test, it is confirmed that each series of financial ETF and energy ETF futures is stationary or integrated at level i.e. I (0). Figure 1 presents the time series plot of RXLF, RSP1, RXLE, RNG1 and RCL1. It is noticed that RXLF, RSP1, RXLE and RCL1 returns fell at the end of 2016 while RNG1 has realized the positive as well as negative stock return. This graphical representation helps us to understand how the series varied over the time. Every series is witnessed with volatility clustering as high changes are followed by high changes and low changes are followed by low changes in these series.

Further, the Granger Causality test is applied to check the direction of transmission of information from financial ETF to energy ETF futures and vice-versa. Table 3 presents the result of Granger Causality. There is bidirectional causality between RXLF and RCL1 at 5% significance level. RXLF does not Granger cause RNG1 and vice versa. Similarly, RXLE does not Granger cause RCL1 and RNG1 while there is bidirectional causality between RXLE and RSP1. In sum, we observe that there is a possibility of transmission of volatility from RXLF to RCL1 and from RXLE to RSP1 and vice versa while the study finds evidence of unidirectional transmission of information from RXLF to RSP1.

Table 2: Summary Statistics

	RXLF	RSP1	RCL1	RNG1	RXLE
Mean	0.0005	0.0005	0.0003	-0.0001	0.0001
Std. dev	0.0171	0.0112	0.0246	0.0316	0.0170
Minimum	-0.1502	-0.1095	-0.2822	-0.1805	-0.2249
Maximum	0.1439	0.0935	0.3196	0.2677	0.1487
Skewness	-0.0573	-0.6239	0.1684	0.7856	-0.8454
Kurtosis	10.9283	10.1094	27.7083	5.5860	16.2300
ARCH Test	0.0040	0.0000	0.0000	0.0000	0.0003
JB Test	20012	17384	126.39	5642.7	44609

Sig. value	0.0000	0.0000	0.0000	0.0000	0.0000
ADF Test	0.0000	0.0000	0.0000	0.0000	0.0003
PP Test	0.0010	0.0000	0.0000	0.0001	0.0000
Nobs	4016	4016	4016	4016	4016

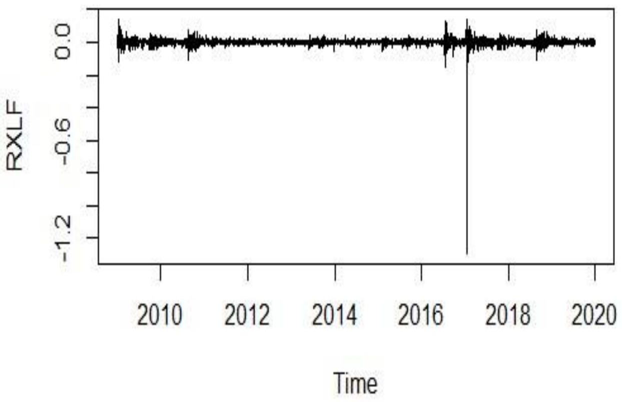
Notes: The table provides descriptive statistics of constituent variables under examination. Std. dev is standard deviation, JB test is Jarque-Bera test for normality, ADF is Augmented Dickey Fuller test while PP is Philips and Perron test for checking the stationarity.

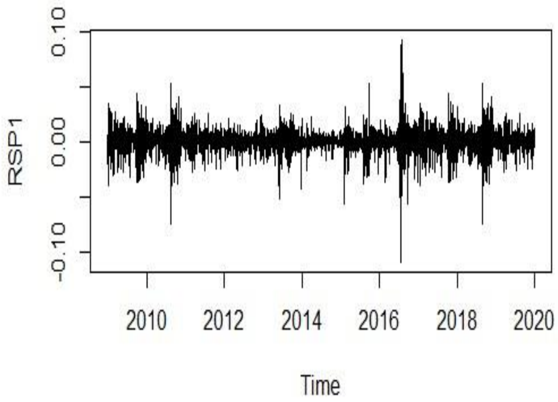
Table 3: Granger Causality Result

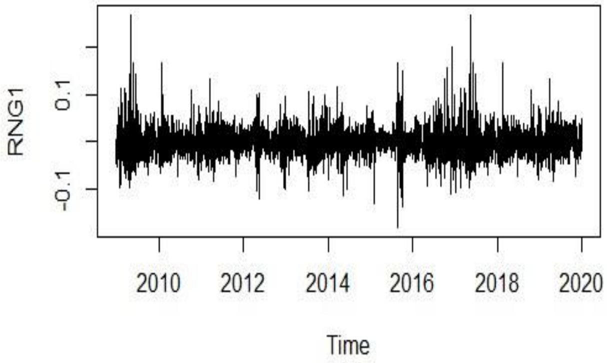
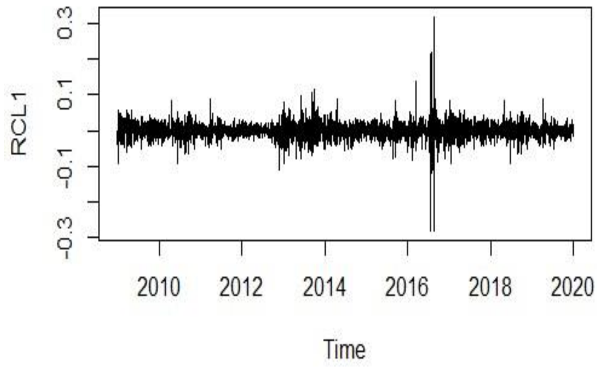
Null Hypothesis	F-value	Probability
RXLF does not Granger cause RCL1.	4.0013	0.04556 **
RCL1 does not Granger cause RXLF.	8.1868	0.03275 **
RXLF does not Granger cause RNG1.	4.0013	0.5156
RNG1 does not Granger cause RXLF.	1.1868	0.19540
RXLF does not Granger cause RXLE.	1.9605	0.16160
RXLE does not Granger cause RXLF.	0.0805	0.6916
RSP1 does not Granger cause RCL1.	1.6993	0.1005
RCL1 does not Granger cause RSP1.	0.4876	0.4851
RSP1 does not Granger cause RNG1.	2.8037	0.09416
RNG1 does not Granger cause RSP1.	0.034	0.8538
RSP1 does not Granger cause RXLE.	2.578	0.0313**
RXLE does not Granger cause RSP1.	3.1643	0.0132**

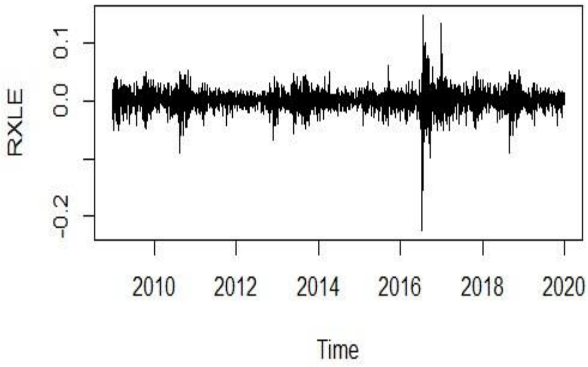
Notes: we check the unidirectional and bidirectional Granter causality test for cause and effect.
*** Significant at 1 percent; ** Significant at 5 percent; * Significant at 10 percent

Figure 1: Time series plot of constituent series


RXLF
0.0
-0.6
-1.2
2010
2012
2014
2016
2018
2020
Time


RSP1
0.10
0.00
-0.10
2010
2012
2014
2016
2018
2020
Time


RNG1
0.1
-0.1
2010
2012
2014
2016
2018
2020
Time

RCL1
0.3
0.1
-0.1
-0.3
2010
2012
2014
2016
2018
2020
Time



4.2 Result of Dynamic conditional correlation

Next, we apply dynamic conditional correlation (DCC) GARCH to examine the spillover from financial ETF futures to energy ETF futures. We applied bivariate dynamic conditional correlation (DCC) GARCH presented in table 3. The table consists of spillover results from RXLF to RCL1, RXLF to RNG1, RXLF to RXLE, RSP1 to RCL1, RSP1 to RNG1 and RSP1 to RXLE. Referring to the results of spillover from RXLF to RCL1, overall mean and constants are represented by "mu" and "omega". "alpha 1" and "beta 1" signify the autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) respectively. The alpha shows whether there is volatility in short run or not which is based on the previous disturbances or error terms. GARCH represents the persistence in the volatility that measures the impact of a shock on conditional correlation for the long run. Individually, the alpha1 and beta1 are positive and significant at a 5% significance level which confirms the persistence of volatility. We observe that the sum of alpha1 and beta1 of both series is less than one which shows time decay over time in volatility persistence. The sum of alpha and beta of RXLF and RCL1 are 0.9809 and 0.9882 respectively. It indicates that

RXLF has fast decay in volatility persistence than RCL1. Further, dcca 1 and dccb 1 denotes the parameters of the dynamic conditional correlation. The coefficients of dcca 1 and dccb 1 are positive and significant at 5% significance level. It reveals that there is spillover or transmission of information in short run and long run. Turning to the spillover from RXLF to RNG1, we find evidence of persistence in the volatility as alpha 1 and beta 1 of both series (RXLF and RNG1) are significant at 5% significant level. The sum of coefficients of alpha is less than 1 which confirms that there is time decay. Notably, RXLF is witnessed with fast time decay because the summation of coefficients of RXLF (0.9809) is less than the summation of coefficients of RNGI (0.9895). The dcca1 parameter is positive and significant while the dccb1 is not significant. It ensures the evidence of short run and long run spillover or transmission of information from RXLF to RNG1. It is worth noting that the summation of dcca1 and dccb1 is less than 1, therefore, dynamic conditional correlation is assumed to be mean reverting. As regards with DCC from RXLF to RXLE, the coefficients (alpha 1 and beta 1) of RXLF and RXLE are positive and significant. It indicates that there is short term and long-term persistence of the volatility. The sum of coefficients of both series is less than 1 which confirms the time decay in the series. The dcca1 and dccb1 parameters are positive and significant, hence, we find the existence of short term and long term spillover from RXLF to RXLE.

Further, spillover from RSP1 to RCL1 has been checked. The alpha 1 and beta 1 of RSP1 and RCL1 are positive and significant. We find evidence of short run and long run volatility persistence in both series. The sum of their coefficients is 0.9814 and 0.9882 respectively, hence, there is fast decay of volatility persistence in RSP1 compared to RCL1. There is spillover or transmission of information of transmission from RSP1 to RCL1 as the dcca 1 and dccb 1 are positive and significant. Additionally, we examine spillover from RSP1 to NG1 and RSP1 to RXLE. The coefficients of each series are positive and significant, and their sum is less than one. The result confirms the short run and long run volatility persistence in each series. Referring the spillover results from RSP1 to RNG1, we observe that the dcca 1 is positive but not significant which indicates that there is no spillover or no transmission of information in short run while there is the existence of long run spillover as dccb 1 is positive and significant.

At last, turning to the results of spillover from RSP1 to RXLE, we find spillover neither in short run nor in long run. The sum dcca 1 and dccb 1 is less than 1 which indicates that the dynamic conditional correlation is mean reverting. Further, we apply Sign Bias test to check the asymmetry in volatility. The p-value of the Sign-Bias test is insignificant which confirms

the rejection of null hypotheses (Ho: There is asymmetry in the volatility of a series). Therefore, there is no requirement of asymmetrical dynamic conditional correlation (DCC).

Table 4: Results of pairwise DCC of constituent series

DCC from RXLF to RCL1				
	Estimate	Std. Error	t-statistics	P-value
[RXLF].mu	0.0008	0.0002	4.5922	0.0000
[RXLF].omega	0.0000	0.0000	0.7255	0.4681
[RXLF].alpha1	0.1424	0.0179	7.9665	0.0000
[RXLF].beta1	0.8385	0.0416	20.1358	0.0000
[RCL1].mu	0.0005	0.0002	2.4772	0.0132
[RCL1].omega	0.0000	0.0000	1.9282	0.0538
[RCL1].alpha1	0.0972	0.0192	5.0539	0.0000
[RCL1].beta1	0.8910	0.0193	46.2553	0.0000
[Joint]dcca1	0.0388	0.0039	9.9290	0.0000
[Joint]dccb1	0.9591	0.0042	226.9941	0.0000
DCC from RXLF to RNG1				

	Estimate	Std. Error	T-Statistics	P-value
[RXLF].mu	0.0008	0.0002	4.5898	0.0000
[RXLF].omega	0.0000	0.0000	0.7250	0.4685
[RXLF].alpha1	0.1424	0.0178	7.9887	0.0000
[RXLF].beta1	0.8385	0.0417	20.1066	0.0000
[RNG1].mu	0.0000	0.0004	-0.0055	0.9956
[RNG1].omega	0.0000	0.0000	1.0950	0.2735
[RNG1].alpha1	0.0740	0.0248	2.9859	0.0028
[RNG1].beta1	0.9155	0.0057	160.6857	0.0000
[Joint]dcca1	0.0375	0.0178	2.1002	0.0357
[Joint]dccb1	0.4780	0.2898	1.6498	0.0990
DCC from RXLF to RXLE				
[RXLF].mu	0.0008	0.0002	4.5922	0.0000
[RXLF].omega	0.0000	0.0000	0.7255	0.4681
[RXLF].alpha1	0.1424	0.0179	7.9665	0.0000
[RXLF].beta1	0.8385	0.0416	20.1358	0.0000
[RXLE].mu	0.0005	0.0002	2.4772	0.0132
[CL1].omega	0.0000	0.0000	1.9282	0.0538
[RXLE].alpha1	0.0972	0.0192	5.0539	0.0000
[RXLE].beta1	0.8910	0.0193	46.2553	0.0000
[Joint]dcca1	0.0388	0.0039	9.9290	0.0000
[Joint]dccb1	0.9591	0.0042	226.9941	0.0000
DCC from RSP1 to CL1				
[sp1].mu	0.0008	0.0001	6.1684	0.0000
[sp1].omega	0.0000	0.0000	1.0793	0.2805
[sp1].alpha1	0.1769	0.0197	8.9983	0.0000
[sp1].beta1	0.8045	0.0243	33.1224	0.0000
[CL1].mu	0.0005	0.0002	2.4792	0.0132
[CL1].omega	0.0000	0.0000	1.9216	0.0547
[CL1].alpha1	0.0972	0.0193	5.0461	0.0000
[CL1].beta1	0.8910	0.0193	46.1105	0.0000
[Joint]dcca1	0.0448	0.0049	9.0526	0.0000
[Joint]dccb1	0.9540	0.0051	186.1126	0.0000
DCC from RSP1 to NG1				
[RSP1].mu	0.0008	0.0001	6.1629	0.0000
[RSP1].omega	0.0000	0.0000	1.0856	0.2776
[RSP1].alpha1	0.1769	0.0197	8.9940	0.0000

[RSP1].beta1	0.8045	0.0239	33.6584	0.0000
[RNG1].mu	0.0000	0.0004	-0.0055	0.9956
[RNG1].omega	0.0000	0.0000	1.0952	0.2734
[RNG1].alpha1	0.0740	0.0248	2.9862	0.0028
[RNG1].beta1	0.9155	0.0057	160.8183	0.0000

[Joint]dcca1	0.0028	0.0037	0.7686	0.4422
[Joint]dccb1	0.9841	0.0258	38.1849	0.0000
DCC from RSP1 to RXLE				
[RSP1].mu	0.0000	0.0004	-0.0055	0.9956
[RSP1].omega	0.0000	0.0000	1.0947	0.2737
[RSP1].alpha1	0.0740	0.0248	2.9844	0.0028
[RSP1].beta1	0.9155	0.0057	160.8932	0.0000
[RXLE].mu	0.0005	0.0002	2.4789	0.0132
[CL1].omega	0.0000	0.0000	1.9270	0.0540
[RXLE].alpha1	0.0972	0.0192	5.0539	0.0000
[RXLE].beta1	0.8910	0.0193	46.2229	0.0000
[Joint]dcca1	0.0073	0.0026	2.8352	0.0046
[Joint]dccb1	0.9881	0.0048	207.1377	0.0000

Notes: This table incapsulates bivariate dynamic conditional correlation (DCC)-GARCH. The table consists of spillover results from RXLF to RCL1, RXLF to RNG1, RXLF to RXLE, RSP1 to RCL1, RSP1 to RNG1 and RSP1 to RXLE. *** Significant at 1 percent; ** Significant at 5 percent; * Significant at 10 percent

4.3 Portfolio weight and hedge ratio

After investigating the spillover from financial exchange traded funds (ETF) futures to energy exchange traded funds (ETF) futures, portfolio weight and hedging ratio are calculated considering the series of conditional variance and conditional covariance derived from symmetrical DCC-GARCH. Creating an optimal portfolio by managing the risk needs a temporal covariance matrix. We calculate optimal portfolio weights to mitigate the risk efficiently in the financial ETF futures and energy ETF futures. In addition, we compute hedge ratios to design the strategy of optimal hedging. To reduce the risks without decreasing expected returns, we can build a portfolio of financial ETF futures and energy ETF futures. We present that a portfolio investor hedges the exposure to financial ETF futures movements by investing their funds in energy ETF futures. For the portfolio weight and hedging, we apply Kroner and Ng (1998) and Kroner and Sultan (1993) respectively. The mean of portfolio weight indicates the optimal allocation of financial ETF futures to energy ETF futures to reduce the portfolio risk without changing expected returns. Further, the mean of the hedge ratio shows that investors can take either a short or long position for the constituent series. Table 5 presents the summary of portfolio weights and hedge ratio of financial ETF futures (RXLF, RSP1) and energy ETF futures (RCL1, RNG1 and RXLE). Referring to the results of summary of portfolio weights presented in table 5, it ranges from 0.024 to 0.232 which are assigned to the SP1/NG1 and SP1/XLE respectively; lowest weight 0.024 signifies that for a portfolio of $1, 2 cents has to be invested in SP1 and remainder 98 ($1-W_{jit}$) cents must be invested in NG1. Comparatively, high weights (0.232) indicate that 23 cents must be invested in SP1, and the rest of the 77 cents ($1-W_{jit}$) should be invested in XLE.

Table 5: Summary statistics of portfolio weight and hedge ratio

Portfolio Weights				
Series	**Mean**	**Std. Dev**	**Min**	**Max**
RXLF/RCL1	0.1684	0.2001	-0.3976	0.6341
RXLF/RNG1	0.0318	0.0372	-0.1635	0.2569
RXLF/RXLE	0.2156	0.3440	-0.2953	0.8844
RSP1/RCL1	0.1684	0.2002	-0.3975	0.6343
RSP1/RNG1	0.0244	0.0079	0.0062	0.0478
RSP1/RXLE	0.2320	0.3697	-0.3365	0.935
Hedge Ratio				
Series	Mean	St Dev	Min	Max
RXLF/RCL1	0.0373	0.0701	0.0070	1.0488
RXLF/RNG1	0.0428	0.0352	0.0115	0.34563
RXLF/RXLE	0.0268	0.0540	0.0048	0.8132

RSP1/RCL1	0.0133	0.0196	-1.010	19.4078
RSP1/RNG1	0.0303	0.0246	0.0077	0.3160
RSP1/RXLE	0.0191	0.0400	0.0027	0.6636

Notes: This table presents the portfolio weight and hedging ratio of constituent series based on conditional variance and conditional covariance using symmetrical DCC-GARCH.

Further, we compute the hedge ratio proposed by Kroner and Sultan (1993) to mitigate the risk of the portfolio (financial ETF futures and energy ETF futures) presented in Table 5. We consider by how much a long position of $1 in financial ETF futures can be hedged by a short position in energy ETF futures. Long position signifies “buy” whereas short position indicates “sell”. We observe that the average optimal hedge ratio of the RXLF/RNG1 pair (0.0428) is the most expensive while the cheapest hedging strategy is of the RSP1/RCL1 pair (0.0133). The optimal hedge ratio of RXLF/RNG1 signifies that a $1 long position in financial ETF futures should be hedged shorting an investment of energy ETF futures by 4 cents to minimize the risk. Similarly, the hedge ratio of RSP1/RCL1 shows that the volatility in the portfolio can be hedged holding $1 long position in RSP1 by 1 cent investment in RCL1. To be precise, the hedging costs of the RXLF investments undertaking the short position in RNG1 is high than rest of the pairs.

5. Conclusion and policy implications

ETF is considered as one of the tradable assets that tracks an index reflecting the economic condition of the underlying sector. It has a potential catalyst to furnish systematic reduction of risk for the portfolio and is preferred more by short-horizon liquidity traders. The popularity of the financial ETF futures has grown with an increase in the adoption of standard ETF. On the other hand, due to the rapid development and huge demand for energy products, investors prefer the energy ETF futures. Derivative market hedgers, further, want to minimize the risk by adopting an appropriate hedging strategy with portfolio weight and optimal hedge ratio. This paper investigates the spillover effect from financial ETF to energy ETF and builds optimal portfolio weight and hedge ratio to minimize the risk.

We employ Granger causality and dynamic conditional correlation using daily data extending from April 2, 2009, to November 23, 2020. The findings of the study have been derived from the Granger causality test that highlights the unidirectional causality flow from RXLF to RSP1 and bidirectional causality between RXLF and RCL1 ETFs futures funds. The rest of the variables do not have cause and effect relationship. In addition, based on the results of dynamic conditional correlation, the study confirms the spillover effect between RXLF and RCL1, RXLF and RXLE, RSP1 and RCL1, and lastly, between RSP1 and RXLE. These results were measured for both short- and long-term volatility movements. In this regard, the present study determines the spillover effect from RXLF to RNG1 is presented in the short term while the volatility spillover impact between RSP1 and RNG1 is shown in long term. The study validates the findings of Chang et al., (2018) and Lau et al., (2017). Based on spillover findings, the study suggests a risk hedging framework by calculating the portfolio weight and optimal hedging ratio for investors investing in ETFs without reducing their expected return. The portfolio weight ranges from 0.024 to 0.232 which are assigned to the SP1/NG1 and SP1/XLE respectively. Referring to the result of the optimal hedge ratio proposed by Kroner and Sultan (1993), we notice that the average optimal hedge ratio of RXLF/RNG1 pair (0.0428) is most expensive while the cheapest hedging strategy is of RSP1/RCL1 pair (0.0133).

The research contributions of the present study are threefold: First, the study contains broad proxies of financial ETF futures (financial select sector SPDR fund, Generic 1st S&P 500 index futures) and energy ETF futures (Generic 1st crude oil WTI futures, Generic 1st natural gas futures and energy select SPDR fund) to assess the spillover effect. This will help upcoming researchers to further examine the volatility, co-movement, and pricing of these securities. This will further help in determining the various hedging and trading strategies involving these ETFs (Lau et al., 2017; Roy and Roy, 2017). The second contribution of the present study is the confirmation of short- and long-term volatility (risk) spillover effects between the financial sector and the energy sector. This will help the institutions, fund managers, investors to understand the arbitrage opportunities in both the markets due to mispricing of securities or high volatility in various periods. This will also help banks and oil firms to hedge their exposure in these markets by using ETFs as a vehicle of diversification (Zhu and Singh, 2016; Ben David et al., 2017). Further, findings related to optimal hedge ratio and portfolio weights of ETFs will offer investors and fund managers access to a diversified portfolio of assets that can be used to hedge volatility risk in the financial and energy sector in the short and long term. Finally, findings related to unidirectional or bidirectional causality will help the investors to understand price co-movements and the causal effect between the ETFs. For example, unidirectional causality between SPDR fund and index fund suggests that the volatility of SPDR fund should be considered as an additional source of risk (volatility) while making investment decisions in index funds by institutional investors, banks, policymakers, fund managers (da Costa Neto et al. 2019). Similarly, bidirectional causality for example between SPDR fund and Crude Oil ETF reflects both as a risk for each other that affect investment returns and decisions of investors. It has two policy implications. First, our result indicates the spillover or dynamic connectedness from financial ETF futures to energy ETF futures. The ETF exchange must know this fact and monitor the pricing accordingly concerning the demand and supply gap in ETF market. This can be used to suggest diversification strategies to investors and identify them as an additional source of systematic risk (Ben- David et al. 2018; Aromi and Clements, 2019). Second, it furnishes the hedging across the ETF tradeable asset due to which an investor knows how much they should invest in financial ETF futures and energy ETF futures. Apart from the investors, regulators and policymakers must be aware of dynamic linkages and spillover of the volatility among constituent variables.

5.1 Limitations and Future Scope of Work

The present study includes only US ETF futures for the analysis purpose based on dynamic conditional correlation, optimal portfolio weight, and optimal hedge ratio. Further studies may enhance these results by testing the causal effect among various developed and developing economies. Furthermore, upcoming research may assess the spillover effect between both spot and futures markets. The findings of the study may be elaborated by examining the spillover by splitting the data in different periods like before and after great financial crisis or during after the COVID19 pandemic so as to gauge if the relationships change due to such crises.

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