3

DYNAMIC VOLATILITY AND SHOCK INTERACTIONS BETWEEN OIL AND THE U.S. ECONOMIC SECTORS

Geoffrey Ngene

Assistant Professor of Finance. Stetson School of Business and Economics. Mercer University

Jennifer Brodmann

Doctoral Candidate. Department of Economics and Finance. University of New Orleans

M. Kabir Hassan

Corresponding Author. 2016 IDB Laureate in Islamic Banking and Finance. Professor of Finance and Hibernia Professor of Economics and Finance and Bank One Professor in Business. Department of Economics and Finance. University of New Orleans

https://*doi.org/10.26870/jbafp.2018.01.002*

Abstract

This study examines (i) the dynamic shocks and volatility interactions between each of the eleven U.S. economic sectors and the oil market; (ii) risk-minimizing optimal capital allocations between each sector and oil; and (iii) the hedging effectiveness resulting from the inclusion of oil in each sector portfolio.

Using weekly data spanning the period June 1994 through February 2016, we document the following regularities: (i) the conditional correlation between each sector and the oil market is time-varying and slowly decaying; (ii) there is either volatility or shock transmission from oil to each sector but not the reverse; and (iii) investors can minimize and hedge risk by allocating a portion of their wealth to oil commodities and forming a portfolio consisting of sector stocks and oil commodities. However, they will need to overweight their investment in sector stocks. Our findings indicate that oil commodities offer diversification potential to U.S. investors holding sector portfolios such as sector ETFs and mutual funds. Further, the risk parity portfolio weights significantly differ from the capital allocation weights.

Keywords

Oil Market; Sectors; CCC model; EDCC-GARCH; portfolio diversification

JEL Classification: G14, G15, E3

I. INTRODUCTION

The increase in integration and volatility of financial markets has made equity and oil prices increasingly sensitive to innovations such as deregulation, political instability, political-economic events, financial crashes, and investors' psychological expectations (Yu et al. 2008). The financialization of oil commodities through the creation of oil futures, options, and swap agreements has attracted global investors who are increasingly interested in holding oil-based financial instruments as investments, contrary to oil's traditional role of hedging risk and supporting "real" economic activity (Vivian and Wohar, 2012). This development has increased liquidity as well as volatility in the oil market. For example, Brent crude oil was priced at $23.95 in January 2000 but spiked to reach an all-time high price per barrel at $145.61 in July 2008. Similarly, in June 2014 the Brent crude oil price was $126.62, but in January 2016 the price dipped to a low of $27.75. These wild swings in price and heightened volatility have generated keen interest in the analysis of volatility in the oil market and how it affects the equity market. The demand-side and supply-side shocks to the oil market can also affect the stock market. According to Hamilton (1996) and Kilian and Park (2009), a demand-side shock or increase in oil prices due to economic expansion (leading to increased oil demand for production and construction) will positively impact the performance of the stock market. However, a supply-side shock resulting from a cutback in the supply of oil by OPEC countries, geopolitical factors, or instability in the Middle East will dampen the performance of the stock market. Therefore, there are volatility and shock interactions between the oil and equity markets.

According to Ross (1989) and Tauchen and Pitts (1983), the flow of information among security markets or financial assets is the key determinant of the volatility of asset prices. Volatility and shock interactions between oil markets and sector equities exist because oil (as a commodity) and economic sectors share mutual information. Investors may also use oil futures and sector equities as imperfect substitutes during portfolio adjustments and allocation decisions. Therefore, shocks and volatility in sector equity (oil market) can regularly trigger reactions in oil (sector market). This study models such interactions using the newly developed Extended Dynamic Conditional Correlation (EDCC-GARCH) model to gain insights into the behavior and interrelationship between sector equity and the oil market as well as the transmission mechanism between the two markets.

Oil price risk affects almost every economic sector. For example, oil is used in the production of raw materials and is also an important input in the manufacturing sector. Low oil prices may result in reduced utilization of existing assets by energy firms. This increases the risk of impairment of assets, reduction of future cash inflows from assets, and, ultimately, reduction in the value of assets (present value of future cash inflows). A sustained oil price plunge could lead to energy sector bankruptcies, especially by low-margin producers. Failure by oil firms to repay their loans could diminish bank profitability as well as initiate a drop in bank equities. Low oil prices also feed into low inflation, low interest rates, and reduced bank profits.

Reduced future cash inflows will herald a reduction in future capital expenditures, resulting in a loss of jobs, particularly in states with a high concentration of oil-related jobs such as Louisiana, Texas, North Dakota, and Oklahoma. These regions would experience a decline in real estate prices or tepid growth. The decline in oil prices reduces the cost of living due to the decline in driving costs, home heating costs, and lower costs of goods and services due to lower production costs, particularly in the Northeast and Midwest, which are non-oil producing regions. The local economies and housing markets in such regions will receive a jolt from decreased oil prices. Increased disposable income from saving may boost consumer discretionary spending on staples and durable goods as well as services[1]. There is an interesting connection between oil prices and the technology sector. A decline in the oil sector will force small energy firms to invest in oil-drilling technologies such as fracking to compete with large firms and reduce costs or invest in alternative energy sources such as renewable and clean-energy initiatives. An increase in oil prices increases the cost of production and dampens consumer spending due to the increased cost of goods and services. These increased costs also feed into inflation, resulting in an increase in interest rates and cost of capital and thus a decline in prices of financial assets such as stocks and bonds (present value of future cash flows declines as discounting rate increases). Therefore, it is telling that oil prices

1. According to estimates by *The Economist*, a \$40 decline in price per barrel could shift some \$1.3 trillion from producers to consumers via direct savings on transport costs, enabling households to increase discretionary spending on other goods and services.

affect the energy, financial, technology, consumer discretionary, manufacturing, materials, real estate, and utilities sectors, among others.

Our study investigates the magnitude and direction of the effects of past period shocks and conditional volatility of both sector equity and oil returns on the conditional volatility of sector equity and oil returns on an individual basis. The insights gained from investigating the shock and price risk transmission mechanism is particularly important for policymakers, market participants, and researchers. For example, whenever policymakers implement policies geared toward a particular sector of the economy (such as the bailout of major banks in the U.S. during the 2007 to 2009 financial crisis) or oil market, they must consider how the shocks and price risks of each market or asset magnifies or diminishes the conditional volatilities of its substitute financial assets through diverse market conduits. Malik and Hammoudeh (2007) also intimate that the examination of volatility spillovers impacts portfolio and risk management, the design of accurate asset pricing models, and the forecasting of future equity and volatility of oil price returns.

This study contributes to the existing literature in three major ways: (i) by testing the relationship between oil and sector equities using the newly developed Extended Dynamic Conditional Correlation (EDCC) model, hence offering a unified econometric model and modeling improvements; (ii) by extending the sample period to twenty-two years to include the Global Financial Crisis period and increasing the number of U.S. economic sectors to eleven; (iii) by implementing new misspecification tests to justify the use of the EDCC model; and (iv) by offering a detailed analysis of the implications of our results for risk and portfolio management. We offer this insight using the traditional portfolio approach to capital allocation as well as the more recent risk parity portfolio allocations. The rest of our study is organized as follows: Section II reviews the relevant literature; Section III explains the data sources and descriptive statistics; Section IV discusses the econometric methodology used in the study; Section V offers empirical evidence; and Section VI concludes.

II. LITERATURE REVIEW

The influence of oil on equity markets is studied extensively by examining oil and stock markets in different countries and using a variety of empirical methods. So far, existing literature arrives to divergent conclusions. Several research studies confirm that there is a relationship between the oil and stock markets (Basher and Sadorsky, 2006; Daly and Fayyad, 2011; Ghosh and Kanjilal, 2016; Hammoudeh and Choi, 2006; Mensi et al., 2013). Ghosh and Kanjilal (2016) use co-integration techniques and conclude that changes in the international crude oil price have an effect on the Indian stock market. This hypothesis is affirmed in studies focusing on specific oil-producing regions (Arouri and Fouquau, 2009; Arouri et al., 2011; Hammoudeh and Choi, 2006). Arouri, et al.

(2011) use the VAR-GARCH approach and find return and volatility spillovers between oil price and Gulf Cooperation Council (GCC) stock markets. Arouri, et al. (2011) use stock market data from seven economic sectors from 1998 to 2009 and find volatility spillovers between oil prices and sector stock market returns. Hammoudeh and Choi (2006) study the relationship between GCC weekly equity index returns and three global factors (oil price, U.S. S&P 500 index, and U.S. T-bill rate). Their findings suggest that GCC stock markets rise when U.S. stocks rise and that positive oil shocks benefit the majority of GCC markets.

To the contrary, some of the previous research has indicated that there is little or no relationship between the oil and stock market and that there is no hedging benefit from investing in oil. Apergis and Miller (2009) find that international stock market returns have a limited market reaction to oil market shocks. Filis et al. (2011) find that the oil market cannot be used as a means of protection from losses in the stock market. Anoruo and Mustafa (2007), using co-integration techniques, obtain similar findings that suggest there is no diversification benefit from holding assets in oil and stock markets. Sukcharoen et al. (2014) identify weak dependence between oil prices and stock market indices for both oil-importing and oil-exporting countries, excluding the stock market indices in the United States and Canada.

Other research finds that the relationship between oil and stock markets depends upon certain factors, such as origin of the shock and the type of activity sector. Kilian and Park (2009) discover that U.S. real stock market reaction to oil price shocks depends on whether changes in the oil price stem from demand shocks or supply shocks present in the oil market. Faff and Brailsford (1999) examine the Australian industry equity return sensitivity towards oil price from 1983 to 1996. Their results indicate that Oil and Gas Diversified Resources industries have significantly positive oil price sensitivity while Paper and Packaging and Transport industries have significantly negative oil price sensitivity. Arouri and Nguyen (2010) find that the impact on stock returns from changes in oil prices differs depending upon the type of activity sector, which is consistent with Faff and Brailsford (1999). In this paper, we use U.S. oil and stock market data with an extended sample period of twenty-two years, with new misspecification tests to support using the EDCC model.

Previous studies conclude that investing in oil may provide a hedging benefit. Malik and Ewing (2009) utilize bivariate GARCH models to estimate the mean and conditional variance interactions between oil prices and economic sector indices in the U.S. using five economic sectors and find a presence of cross-market hedging. Our paper uses the new EDCC model to determine if such a relationship between oil and stock markets exists, if it is a positive or negative relationship, and if investing in oil can provide a hedging benefit in a two-asset portfolio with investments in oil and eleven industry sectors.

III. DATA

We use weekly data for eleven economic sectors and the oil prices of West Texas Intermediate (WTI) oil. The eleven economic sectors are Consumer Discretionary (CDI), Consumer Staple (CSI), Energy (EGY), Financial (FIN), Healthcare (HCI), Industrial (IND), Materials (MAT), Technology (TEC), Telecommunication (TEL), Real Estate (REST), and Utilities (UTL). The sample period is from June 1994 through February 2016 accounting for 1135 weekly observations, except for Utilities (UTL) and Real Estate (REST), which have 900 and 457 weekly observations respectively.

Panel A in Table 1 shows the descriptive statistics for the eleven economic sectors. The reported statistics in Table 1 reveal that the distributional features of the returns widely vary across the sectors. Excess kurtosis ranges from 4.17 in the Materials (MAT) sector to 11.03 in the Financial (FIN) sector. However, the excess kurtosis of oil (WTI) of 373.71 is the highest among the series, signifying the highest tail risk and fat-tail distribution. The highest (lowest) standard deviation of returns belongs to the Real Estate (Consumer Staple) sector at 4.116 (1.980), but the standard deviation of the oil returns of 4.262 still exceeds that of each of the eleven sectors. The Jarque-Bera (JB) test statistics exceed the asymptotically distributed chi-square critical values, thereby invalidating the assumption of a normal distribution of returns for all sectors and oil. All sectors and oil returns are pigeonholed by statistically material negative skewness, implying that there are more negative returns than positive returns, hence indicating a higher probability of making losses than gains, most notably in the Utilities (UTL) sector. To accommodate these distributional features of returns, we utilize the generalized error distribution (GED) in our econometric model. The Ljung-Box Q-statistic indicates that the first ten weekly linear autocorrelations are statistically insignificant or zero for all sectors except oil. However, the same test using non-linear (squared) returns shows that the first ten weekly autocorrelations are not equal to zero, as the $Q^2(10)$ statistic is significant and rejects the null of zero autocorrelation at the 1% significance level for all sectors and oil returns.

Further, the test of constant variance or homoscedasticity (ARCH test) is rejected at the 1% significance level for the first five and ten autocorrelations of squared residuals. This evidence serves as a preliminary justification for the use of GARCH modeling. Panel B of Table 1 presents the cross-sector correlations and the correlation between each sector and oil returns. The unconditional correlation between any two sectors is significant and highest (lowest) between CDI and IND at 0.918 (REST and UTL at 0.498). This evidence suggests sector returns provide little or no opportunity for cross-sector hedging and risk diversification. However, the unconditional correlations between each sector and oil returns broadly differ across the pairs. In fact, the unconditional correlations are not only insignificant, they are as low (high) as –0.039 (0.045), providing initial evidence of a potential diversification benefit from the formation of a sector-oil portfolio. We shall explore this issue in a later portion of the study.

Table 1: Panel A: Descriptive Statistics and Unconditional Correlation Analysis

Variable	Mean	Std. Dev	Range	Skewness	Ex. Kurtosis	Jarque-Bera	ARCH(5)	ARCH(10)	Q(10)	$Q^2(10)$	N
CDI	0.171	2.875	36.212	– 0.519***	5.601***	1543.30***	52.683***	10.667***	17.431	582.738***	1135
CSI	0.202	1.980	27.445	– 0.934***	8.364***	3473.60***	14.466***	7.971***	11.973	103.114***	1135
EGY	0.166	3.317	42.266	– 0.962***	6.625***	2250.80***	21.934***	15.271***	14.675	188.572***	1135
FIN	0.141	3.381	48.37	– 0.140*	11.030***	5757.40***	61.916***	43.558***	9.2485	726.304***	1135
HCI	0.218	2.392	29.015	– 0.851***	6.269***	1995.50***	10.515***	7.4963***	11.247	94.798***	1135
IND	0.171	2.786	31.614	– 0.521***	4.295***	923.84***	42.835***	24.18***	13.608	446.697***	1135
MAT	0.131	3.135	33.564	– 0.544***	4.170***	878.37***	51.568***	30.133***	8.203	555.147***	1135
TEC	0.180	3.804	47.088	– 0.691***	4.813***	1185.70***	17.367***	14.686***	8.884	268.859***	1135
UTL	0.162	2.319	30.325	– 1.300***	10.193***	5233.50***	10.801***	5.735***	5.053	72.536***	1135
REST	0.066	4.116	40.067	– 0.308***	6.135***	723.91***	57.276***	29.573***	7.3794	502.952***	457
TEL	0.036	3.111	40.894	– 0.375***	6.007***	1374.4***	18.558***	18.603***	4.3023	269.156***	900
WTI	0.048	4.262	44.359	– 0.219***	373.710***	373.71***	32.329***	18.974***	41.741***	371.014***	1135

Panel B: Unconditional Correlation between Economic Sectors pairs and between each sector and oil returns

	CDI	*CSI*	*EGY*	*REST*	*FIN*	*HCI*	*IND*	*MAT*	*TEC*	*TEL*	*UTL*
CSI	0.776***										
t-stat	[26.222]										
EGY	0.711***	0.671***									
t-stat	[21.556]	[19.313]									
REST	0.799***	0.590***	0.526***								
t-stat	[28.313]	[15.579]	[13.190]								

Variable	Mean	Std. Dev	Range	Skewness	Ex. Kurtosis	Jarque-Bera	ARCH(5)	ARCH(10)	Q(10)	$Q^2(10)$	N
FIN	0.876***	0.688***	0.661***	0.809***							
t-stat	[38.78]	[20.202]	[18.786]	[29.346]							
HCI	0.758***	0.800***	0.663***	0.574***	0.704***						
t-stat	[24.826]	[28.421]	[18.908]	[14.970]	[21.131]						
IND	0.918***	0.753***	0.784***	0.771***	0.858***	0.747***					
t-stat	[49.508]	[24.430]	[26.915]	[25.811]	[35.557]	[23.977]					
MAT	0.847***	0.679***	0.851***	0.715***	0.764***	0.698***	0.908***				
t-stat	[34.006]	[19.706]	[34.606]	[21.821]	[25.235]	[20.780]	[46.226]				
TEC	0.890***	0.729***	0.756***	0.652***	0.748***	0.743***	0.879***	0.843***			
t-stat	[41.742]	[22.704]	[24.665]	[18.348]	[24.062]	[23.648]	[39.360]	[33.385]			
TEL	0.829***	0.780***	0.707***	0.658***	0.778***	0.736***	0.806***	0.768***	0.787***		
t-stat	31.587]	[26.55]	[21.319]	[18.641]	[26.379]	[23.19]	[29.003]	[25.599]	[27.205]		
UTL	0.608***	0.734***	0.676***	0.498***	0.566***	0.668***	0.630***	0.613***	0.591***	0.682***	
t-stat	[16.317]	[23.043]	[19.554]	[12.243]	[14.643]	[19.139]	[17.315]	[16.533]	[15.619]	[19.896]	
WTI	0.014	0.029	– 0.012	– 0.014	0.045	0.030	0.023	0.006	0.018	0.000	– 0.039
t-stat	[0.292]	[0.625]	[–0.252]	[–0.293]	[0.955]	[0.631]	[0.497]	[0.131]	[0.385]	[0.010]	[–0.840]

Notes: ARCH (5) and ARCH (10) are the Engle (1982) test of constant variance at the 5th and 10th autocorrelation orders. Q (10) and Q^2 (10) are the robust Ljung-Box Q-statistics for returns and squared returns to test linear and nonlinear serial correlations at ten lags. Panel B shows the unconditional correlation between any two sectors and between each sector and WTI oil returns. The numbers in brackets are the corresponding t-statistic (t). *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively.

IV. METHODOLOGY

Shadat and Orme (2016) note that while constant conditional correlation (CCC) models bear simplicity and computational advantages, the surge in the generality of the dynamic conditional correlation (DCC) approach makes it necessary to test the adequacy of the CCC assumption within an MGARCH model for a practical as well as theoretical point of view. Amado and Teräsvirta (2014) also argue that the CCC assumption in CCC multivariate GARCH models such as the CCC-GARCH[2] of Bollerslev (1990) and VAR-GARCH of Ling and McAleer (2003) is overly limiting.

Engle (2002) developed the DCC model, which is a GARCH-type model that captures the dynamics of conditional correlations. The correlation structure of the DCC models can be explained as follows:

$$y_t = \beta X_t + \mu_t \tag{1}$$

$$\mu_t = H_t^{0.5} z_t \tag{2}$$

$$H_t = D_t^{0.5} C_t D_t^{0.5} \tag{3}$$

$$C_t = diag(Q_t)^{-0.5} Q_t diag(Q_t)^{-0.5} \tag{4}$$

$$Q_t = (1 - A - B)Q + A\eta_{t-1}\eta_{t-1}' + BQ_{t-1} \tag{5}$$

$$A + B < 1 \text{ and } A, B > 0 \tag{6}$$

Where y_t is a k-vector of dependent variables; μ_t and z_t are k-vectors of *i.i.d N(0,1)* error terms; β is a *k x m* matrix of parameters; X_t is a m-vector of independent variables including the lags of y_t where necessary; and $H_t^{0.5}$ is the Cholesky factor of the time-varying conditional covariance matrix of H_t.

D_t is a diagonal matrix of conditional variances. C_t is a matrix of conditional quasi-correlations. ηt is a vector of innovations normalized by the conditional standard deviation of returns. Therefore, ηt=D-$0^{.5}_t$ μ_tQ is the weighted average of the unconditional covariance of ηt, hence Q=Cov(ηtηt')=E(ηtηt') and the unconditional mean of Q_t. The non-negative scalars *A* and*B* are the only two principal drivers of the conditional correlation process, affording the DCC a simple parameterization structure, alleviating the computational burden and contemporaneously permitting large dimensional conditional correlations.

By defining C_t in (4), we can derive the log-likelihood function, *l,* of the DCC-GARCH model and further decompose it into (i) the volatility

2. The CCC-GARCH model only permits contemporaneous dependence via conditional correlations which is insufficient for volatility interactions among financial assets.

component, v at time t and (ii) the correlation component c at time t. The two components take the following forms:

$$\ell_{v,t}(\omega) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln\left|V_t\right| - \frac{1}{2}\mu_t^{\prime} V_t^{-1}\mu_t \qquad (7)$$

In (7), $V_t = D_t^2$ while ω represents the volatility parameters. The volatility component is thus maximized with respect to ω. For a bivariate case, the DCC model, a diagonal model which excludes the possibility of volatility spillovers, would maximize the estimation of the following GARCH (1,1) volatility parameters:

$$h_t = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} A_{11} & 0 \\ 0 & A_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} B_{11} & 0 \\ 0 & B_{22} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-1} \end{bmatrix} \qquad (7a)$$

The EDCC-GARCH model is an off-diagonal model which permits the possibility of volatility spillovers. The log likelihood would be maximized in estimation of the following bivariate GARCH (1, 1) volatility parameters:

$$h_t = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-1} \end{bmatrix} \qquad (7b)$$

The correlation component of l is modeled as follows:

$$\ell_{c,t}(\omega,\varpi) = -\frac{1}{2}\ln\left|C_t\right| - \frac{1}{2}\eta_t^{\prime} C_t^{-1}\eta_t + \frac{1}{2}\eta_t^{\prime}\eta_t \qquad (8)$$

Similarly, ϖ in (8) represents the correlation parameters. We maximize (8) with respect to ϖ conditional on the estimates derived from (7). To circumvent Q_t becoming an explosive sequence, the constraints in (6) must be observed in all the iterations while maximizing (7) and (8). It is clear that decomposition of the log-likelihood function into (7) and (8) makes the estimation of the DCC-GARCH model a two-step process. The newly developed extended DCC-GARCH (EDCC-GARCH) model of Nakatani and Teräsvirta (2008a, 2008b, 2009) offers a unified econometric modeling by (i) permitting volatility interactions through off-diagonal elements of B in (7b), (ii) permitting shock interactions through off-between elements of A in (7b), and (iii) generating DCC between any two series.

V. RESULTS AND DISCUSSION

Using the Tse (2000) test, we examine whether the correlation between oil price changes and sector returns is constant, with the null hypothesis being that there is Constant Conditional Correlation (CCC). Table 1 shows the results from the model tested for CCC. The Engle and Sheppard (E-S, 2001) test also examines the null of CCC, but unlike the Tse (2000) LM test, the E-S test is based on various lag orders and on standardized correlation. In this paper, we conduct the test using lag orders of five, ten, fifteen, and twenty. Almost all of the economic sectors, except for consumer staples, reject the null hypothesis using the E-S tests. Table 2 shows the results from these tests. The results confirm that conditional correlation between any economic sector and the oil market is not time-invariant as has been assumed in past studies. Our null of CCC is rejected by either of the two methods or by the E-S method at a different lag order.

Table 2: Constant Conditional Correlation (CCC) and tests of CCC

Variable	CCC	Tse (LM)	ES (5)	ES(10)	ES(15)	ES(20)
CDI	– 0.0169	4.105**	32.157***	35.548***	41.443***	44.842***
CSI	– 0.0169	7.124***	8.835	12.496	21.292	29.027
EGY	– 0.0020	6.819***	51.217***	55.000***	64.977***	69.238***
FIN	– 0.0080	5.803**	33.934***	36.242***	41.720***	43.005***
HCI	– 0.0450	13.324***	23.902***	29.809***	32.991***	35.747**
IND	– 0.0174	7.012***	42.660***	44.389***	48.226***	53.248***
MAT	– 0.0270	5.995**	55.231***	59.396***	62.651***	67.403***
TEC	– 0.0070	6.288**	29.041***	31.353***	35.612***	39.740***
UTL	– 0.0250	7.913***	14.980**	27.525***	29.708**	38.509**
REST	– 0.0490	2.046	10.302	19.059**	21.317	24.448
TEL	– 0.0200	9.140***	47.480***	51.098***	56.706***	61.724***
WTI	– 0.0169	7.124***	8.835	12.496	21.292	29.027

Notes: Constant Conditional Correlation (CCC) tests. Tse (LM) is the LM Test for Constant Correlation of Tse (2000). ES (5)–(20) are the Engle and Shepard (2001) tests for dynamic correlation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

One of the pre-requisites for fitting the EDCC-GARCH model is to carry out misspecification tests to investigate whether indeed causality in conditional variance is extant. We employ three tests, namely the (i) Nakatani and Teräsvirta (NT) test, (ii) the Robust NT (robNT) test, and (iii) HH test of Hafner and Herwatz (2006). The NT test is considered standard or non-robust while the robNT test is robust in the presence of heteroscedasticity. The three tests can generate test statistics for K-dimensional time series data. Further, the test statistics have a chi-square distribution with 2*K* (*K*–

1) degrees of freedom. They are also premised on the null hypothesis of no causality in conditional variance (Nakatani and Teräsvirta, 2009). The results of the three tests are reported in Table 3. We report the test statistics and corresponding p-values. The HH test fails to reject the null of no causality in conditional variance for TEC/oil, UTL/oil, and REST/oil pairs of the series. However, the NT test rejects the null for all sector/oil pairs at either the 1% or 5% significance levels, thereby supporting bi-directional causality in conditional variance of each sector and oil. The robNT test offers mixed evidence as shown by the test statistic and p-values. The general conclusion is that there is bidirectional causality in conditional variance between each economic sector and oil markets. This evidence justifies the use of the EDCC-GARCH model in subsequent analysis.

Table 3: Tests of Volatility interactions between Oil and each of the sectors

Variable	HH test	P-value	NT test	P-value	robNT test	P-value
CDI	22.31***	0.000	86.175***	0.000	8.788*	0.067
CSI	16.548**	0.002	25.086***	0.000	8.563*	0.073
EGY	18.613***	0.001	41.973***	0.000	10.235**	0.037
FIN	8.747*	0.068	50.070***	0.000	6.775	0.148
HCI	28.986***	0.000	62.469***	0.000	9.456*	0.051
IND	36.153***	0.000	101.135***	0.000	6.168	0.187
MAT	27.375***	0.000	57.866***	0.000	3.844	0.427
TEC	6.320	0.176	19.580***	0.001	4.587	0.332
UTL	5.810	0.214	11.051**	0.026	9.353*	0.053
REST	3.147	0.533	10.694**	0.030	8.073*	0.089
TEL	12.989**	0.011	13.095**	0.011	14.070***	0.007

Notes: HH test is the Hafner and Herwatz (2006) test. NT test and robNT tests are the non-robust (standard) and the robust forms of the Nakatani and Teräsvirta (NT, 2009) tests. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 shows the estimates for the EDCC-GARCH model for each of the 11 economic sectors with their corresponding standard error and t-statistic for volatility parameters a_1, a_2, A_{11}, A_{21}, A_{12}, A_{22}, B_{11}, B_{21}, $B_{12,}$ and B_{22} and correlation parameters α and β. The parameters A_{11} (A_{22}) and B_{11} (B_{22}) are similar to the ARCH and GARCH terms of the sector (oil) in a univariate GARCH model. The magnitude of these parameters indicates that the evolution of the conditional covariances is heavily dependent on their past one-period conditional variance as opposed to the lagged normalized innovations. The parameters A_{12} (A_{21}) and B_{12} (B_{21}) are the off-diagonal volatility elements in the EDCC-GARCH model which capture the shock and volatility interactions or causality. Specifically, A_{12} (A_{21}) demonstrates the shock spillover from the sector (oil) to the oil (sector) market. Likewise, B_{12} (B_{21}) demonstrates volatility spillover from each sector (oil) to the oil (sector) market. We note that parameter A_{12} deviates considerably from zero at conventional levels of significance for the Consumer Staple (CSI), Energy (EGY), Healthcare (HCI), Materials (MAT), Technology (TEC), and Real Estate (REST) sectors. This means that the lagged volatility in the oil market has a positive effect on the current week volatility in the Consumer Staple (CSI), Energy (EGY), Healthcare (HCI), Materials (MAT), Technology (TEC), and Real Estate (REST) sectors. Furthermore, the squared innovation or shocks from the oil market in week *t-1* positively induces the volatility of all sectors at week *t* except the Technology (TEC) sector. There is statistically significant shock and volatility spillover from the oil market to the Consumer Discretionary (CSI), Energy (EGY), Healthcare (HCI), Materials (MAT), and Real Estate (REST) sectors, but the magnitude and statistical significance of the contributions of the oil market to each sector differ decidedly. Moreover, the Consumer Staple (CDI), Financial (FIN), Industrial (IND), Utilities (UTL), and Telecommunication (TEL) sectors do not respond to previous period volatility emanating from the oil market.

Table 4: Shock and Volatility Interactions between oil and each sector using EDCC model CDI

Variable		a_1	a_2	A_{11}	A_{21}	A_{12}	A_{22}	B_{11}	B_{21}	B_{12}	B_{22}	α	β
CDI	Estimates	0.113	0.548***	0.164***	0.100**	0.000	0.077	0.770***	0.000	0.258*	0.856***	0.002	0.965***
	Std. Error	0.128	0.039	0.006	0.049	0.020	0.265	0.083	0.029	0.130	0.066	0.016	0.208
	t	0.883	14.143	25.297	2.011	0.007	0.291	9.286	0.006	1.985	13.054	0.127	4.647
CSI	Estimates	0.169**	0.436***	0.131***	0.181**	0.012	0.071	0.778***	0.067***	0.000	0.854***	0.012	0.943***
	Std. Error	0.069	0.042	0.013	0.079	0.021	0.236	0.185	0.023	0.396	0.070	0.024	0.298
	t	2.439	10.263	10.028	2.276	0.559	0.302	4.195	2.855	0.000	12.172	0.509	3.168
EGY	Estimates	0.110	0.979***	0.104***	0.148***	0.001	0.074	0.884***	0.115***	0.005	0.774***	0.006	0.989***
	Std. Error	0.136	0.035	0.008	0.030	0.029	0.449	0.045	0.034	0.092	0.104	0.007	0.017
	t	0.808	27.630	12.757	4.849	0.029	0.166	19.688	3.345	0.059	7.431	0.831	58.064
FIN	Estimates	0.089	0.909***	0.151***	0.093**	0.000	0.100	0.818***	0.002	0.014	0.802***	0.014	0.957*
	Std. Error	0.113	0.036	0.006	0.038	0.017	0.401	0.070	0.034	0.089	0.075	0.018	0.515
	t	0.792	25.345	23.573	2.452	0.001	0.249	11.733	0.063	0.152	10.668	0.767	1.856
HCI	Estimates	0.333*	0.730***	0.193***	0.185*	0.015	0.080	0.690***	0.300***	0.008	0.823***	0.006	0.921***
	Std. Error	0.170	0.060	0.015	0.097	0.032	0.316	0.158	0.030	0.329	0.096	0.035	0.121
	t	1.959	12.261	13.168	1.919	0.457	0.254	4.357	10.146	0.023	8.574	0.171	7.589
IND	Estimates	0.121	0.860***	0.109***	0.115***	0.000	0.096	0.855***	0.023	0.010	0.811***	0.008	0.912***
	Std. Error	0.115	0.030	0.006	0.030	0.018	0.347	0.076	0.031	0.097	0.066	0.026	0.255
	t	1.053	28.843	17.619	3.894	0.004	0.276	11.309	0.731	0.104	12.238	0.308	3.577

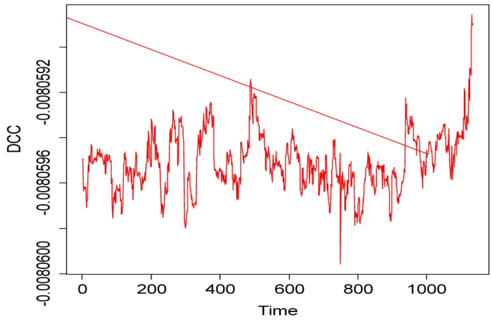
Variable		a_1	a_2	A_{11}	A_{21}	A_{12}	A_{22}	B_{11}	B_{21}	B_{12}	B_{22}	α	β
MAT	Estimates	0.130	0.556***	0.068***	0.103***	0.001	0.085	0.919***	0.243***	0.015	0.830***	0.003	0.984***
	Std. Error	0.080	0.022	0.007	0.027	0.014	0.243	0.047	0.028	0.056	0.057	0.009	0.062
	t	1.629	25.748	9.487	3.796	0.047	0.352	19.573	8.620	0.267	14.554	0.387	15.889
TEC	Estimates	0.136	0.402***	0.091***	0.040	0.007	0.082	0.890***	0.220***	0.001	0.869***	0.003	0.978*
	Std. Error	0.088	0.023	0.009	0.026	0.017	0.179	0.027	0.026	0.040	0.043	0.010	0.533
	t	1.552	17.528	9.733	1.544	0.423	0.458	33.546	8.507	0.028	20.247	0.287	1.834
UTL	Estimates	0.046	0.895***	0.137***	0.114**	0.009	0.099	0.818***	0.002	0.004	0.821***	0.010	0.924*
	Std. Error	0.086	0.048	0.007	0.050	0.014	0.395	0.097	0.032	0.119	0.060	0.030	0.489
	t	0.540	18.769	19.370	2.291	0.637	0.250	8.399	0.054	0.037	13.632	0.335	1.891
REST	Estimates	0.159	0.336***	0.291***	0.170**	0.000	0.110	0.671***	0.224***	0.037	0.861***	0.012	0.852**
	Std. Error	0.255	0.094	0.009	0.076	0.025	0.205	0.060	0.043	0.079	0.066	0.039	0.433
	t	0.624	3.579	31.967	2.245	0.002	0.535	11.111	5.200	0.467	13.140	0.305	1.968
TEL	Estimates	0.113	0.972***	0.120***	0.133**	0.011	0.078	0.850***	0.000	0.000	0.804***	0.002	0.986***
	Std. Error	0.193	0.044	0.016	0.062	0.045	0.502	0.058	0.030	0.124	0.101	0.011	0.195
	t	0.587	22.336	7.481	2.159	0.249	0.155	14.637	0.001	0.000	7.976	0.207	5.054

Table 4 shows the estimates, standard error, and t-statistics for each of the 11 economic sectors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

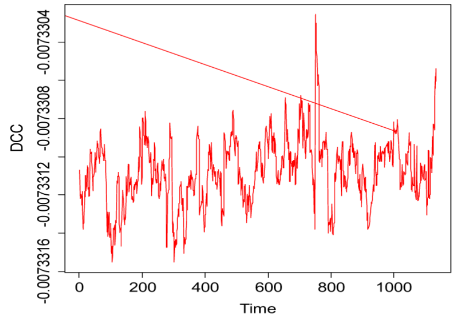
The general inference is that U.S economic sectors respond heterogeneously to past period shocks and volatility originating from the oil market. The correlation persistence parameter ($\alpha+\beta$) is close to one for each sector-oil combination.

This evidence suggests very slow mean-reversion or decay in conditional correlations. However, persistence is weakly significant at the 10% level for Financial (FIN), Technology (TEC), and Utilities (UTL). This indicates a swift update of correlation information by portfolio managers. Figure 1 shows the corresponding graphs for the evolution of the DCC model. We identify a number of observations. First, the correlation structures between each economic sector and oil volatility are starkly different. Therefore, each sector should be considered individually when forming a sector/oil portfolio. Such sector/oil portfolios would have different risk and hedge ratios due to different correlations. Second, correlation is time-varying and can swing between positive and negative realms. The implication for this evidence is that investors need to constantly monitor and rebalance their portfolios to improve risk-adjusted returns. Further, the use of constant conditional correlation in portfolio and risk management may be misleading and erroneous. The shifts between low positive and negative correlations support evidence in Table 1 of low positive and negative unconditional correlations between sector and oil returns and in Table 2 of a slightly negative CCC for all economic sectors, suggesting that an increase in the volatility of oil (sector) returns reduces the volatility of sector (oil) returns.

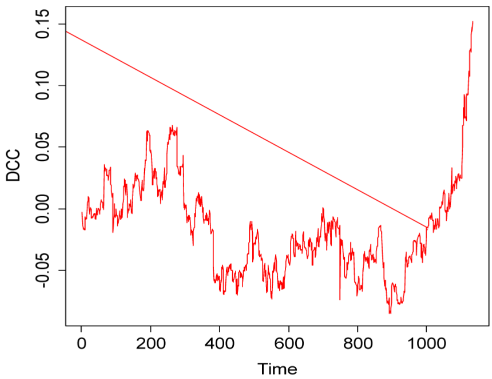
Figure 1: EDCC-GARCH Graphs



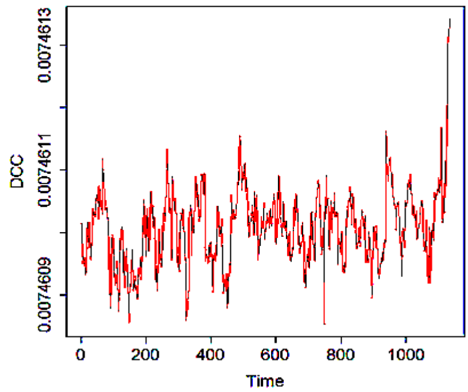
DCC between EGY and WTI



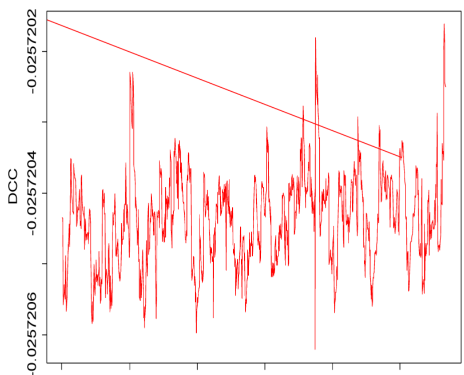
DCC between FIN and WTI

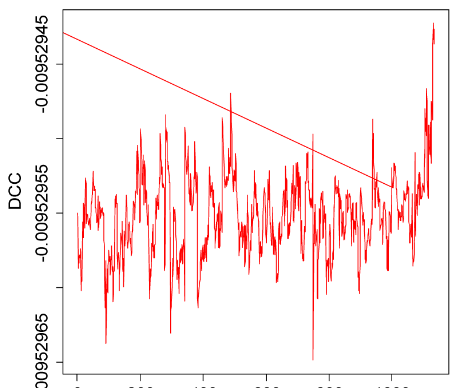


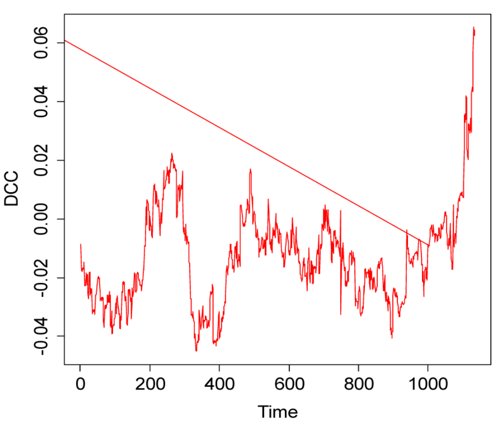
DCC between HCI and WTI

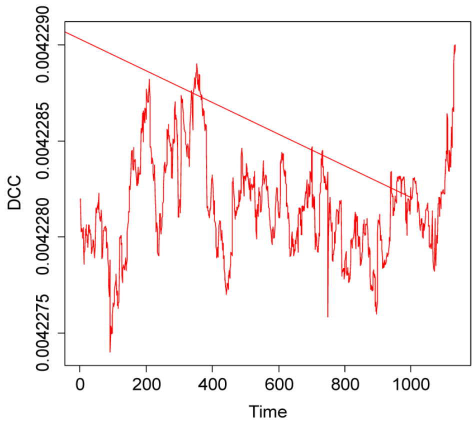


DCC between IND and WTI

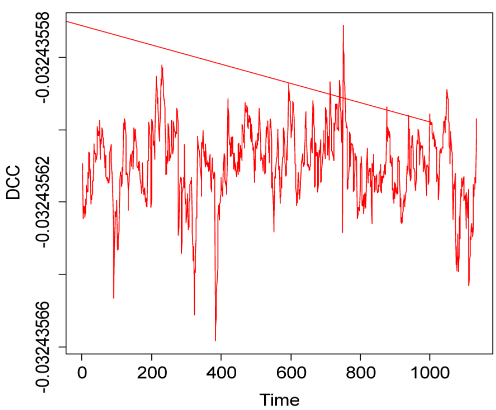




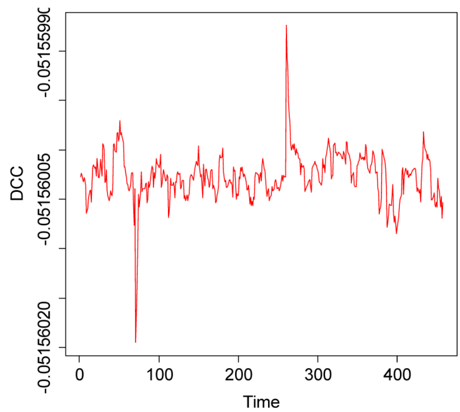




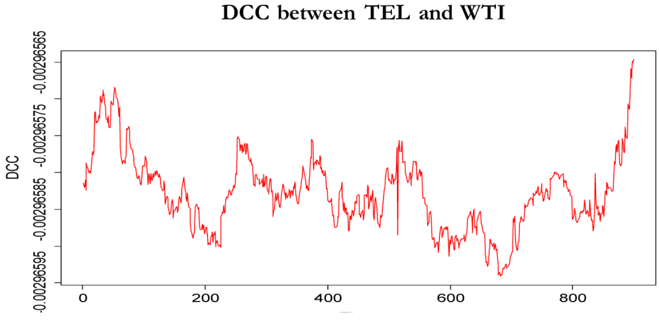
DCC between UTL and WTI



DCC between REST and WTI



DCC between TEL and WTI



1. PORTFOLIO AND RISK MANAGEMENT

We utilize the evidence from our bivariate analysis to assess portfolio allocation and hedging implications. The purpose of this assessment is to show the risk faced by investors who invest in U.S. equity sector indices and how such price risk can be hedged. An investor holding a sector-based portfolio can hedge the equity position against unfavorable changes in oil prices to improve risk-adjusted returns of a sector/oil portfolio. According to Kroner and Ng (1998), the optimal holding or risk-minimizing weight at period t in oil, $W_{o,t}$, given a $1 sector/oil portfolio can be derived as follows:

$$W_{o,t} = \frac{\sigma_s^2 - \sigma_{o,s}}{\sigma_s^2 + \sigma_o^2 - \sigma_{o,s}} \tag{9}$$

In (9), $\sigma_o^{\ 2}$, $\sigma_s^{\ 2}$, and $\sigma_{o,s}$ are the conditional variance of oil returns, conditional variance of sector returns, and conditional covariance between oil and sector returns, respectively. The accompanying constraints for (9) are as follows:

$$W_{o,t} = \begin{cases} 0 & \text{if } W_{o,t} < 0 \\ W_{o,t} & \text{if } 0 \le W_{o,t} \le 1 \\ 1 & \text{if } W_{o,t} > 1 \end{cases} \tag{10}$$

Table 5a reveals that the optimal weights for oil and sector equity differ extensively across U.S. economic sectors. The sector equity in the $1 hedged sector/oil portfolios ranges from 58.4 cents (41.6 cents) investment in TEC sector (oil) to 80.2 cents (19.8 cents) investment in CSI sector (oil). These allocations enable the investors to minimize portfolio risk while maintaining the same level of portfolio returns. We also find $W_{o,t} < W_{s,t}$ for all sectors, indicating that the optimal sector/oil portfolio requires overweighting the apportionment of the $1 investment to the side of the U.S. sector equity portfolio. Therefore, since there are uni-directional shocks and volatility transfers from oil to sector stocks, any change in the oil prices would negatively affect the risk-adjusted returns of the sector/oil hedged portfolios.

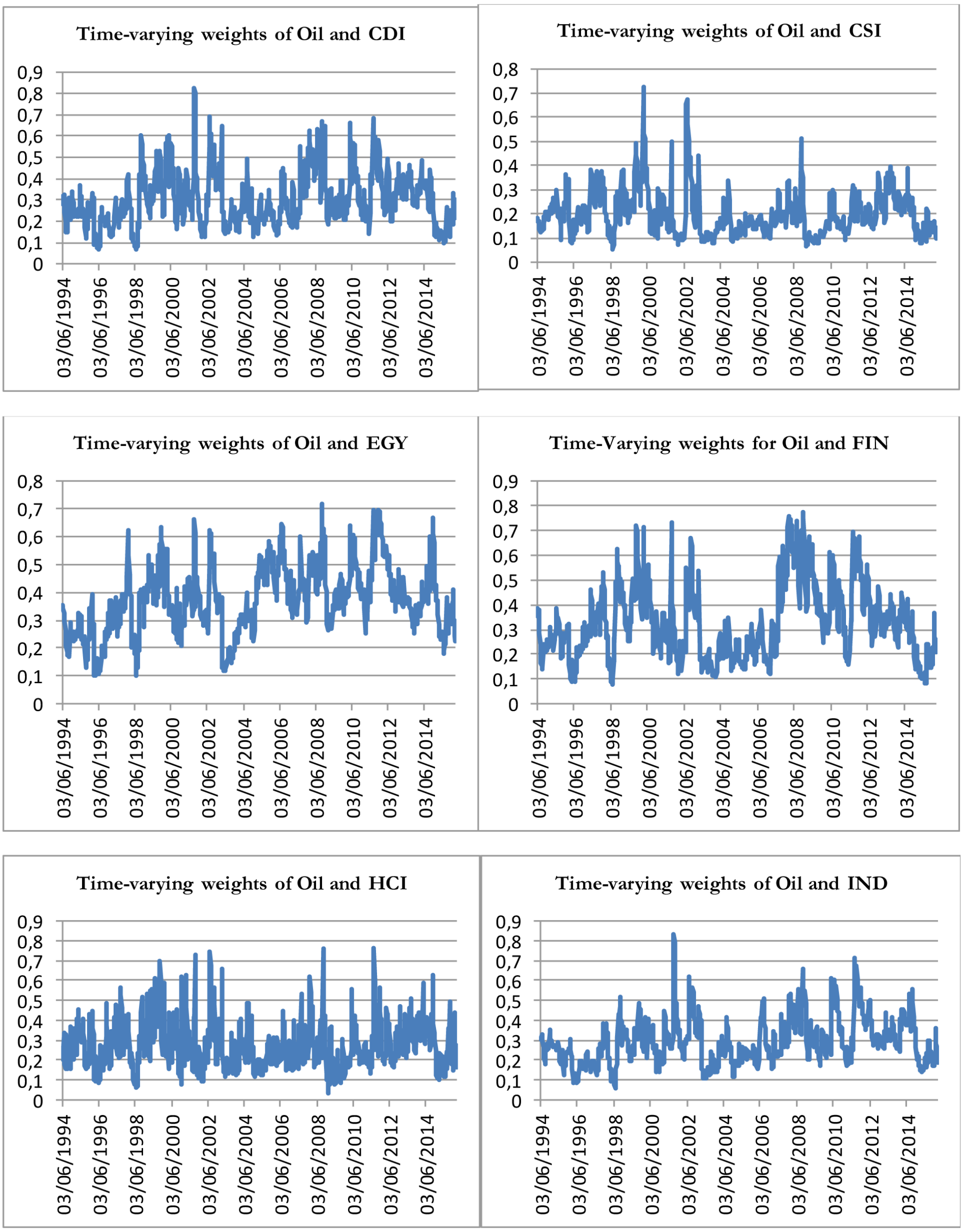
Table 5a: Optimal allocation, portfolio risk and returns and hedge ratio

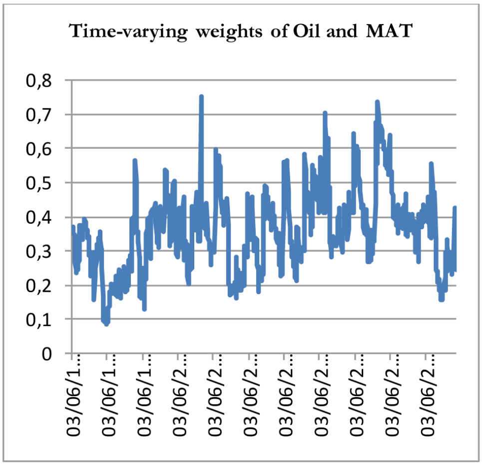
Portfolio	$W_{o,t}$	$W_{s,t}$	EAR	$\sigma_{p.a}$	$\sigma_{o,s}$	ER(p)	σ_p	ER(p)/σ_p	H.R.
CDI/oil	0.301	0.699	9.280	20.729	0.0172	7.249	17.191	0.422	0.0025
CSI/ oil	0.198	0.802	11.067	14.277	–0.1350	9.377	12.965	0.723	–0.0373
EGY/oil	0.372	0.628	9.012	23.922	0.6017	6.602	18.886	0.350	0.0618
FIN/oil	0.326	0.674	7.583	24.384	0.0589	5.937	19.248	0.308	0.0072
HCI/oil	0.268	0.732	11.997	17.250	–0.3658	9.461	15.071	0.628	–0.0698
IND/oil	0.292	0.708	9.268	20.092	0.0096	7.301	16.819	0.434	0.0014
MAT/oil	0.357	0.643	7.070	22.610	–0.2390	5.450	18.210	0.299	–0.0234
TEC/oil	0.416	0.584	9.803	27.430	0.1277	6.779	20.496	0.331	0.0106
UTL/oil	0.235	0.765	8.779	16.723	–0.1054	7.311	14.689	0.498	–0.0222
REST/oil	0.401	0.599	3.471	29.682	–0.9719	3.095	21.622	0.143	–0.0738
TEL/oil	0.321	0.679	1.913	22.434	–0.1131	2.112	18.146	0.116	–0.0146
Oil(WTI)			2.533	30.732					

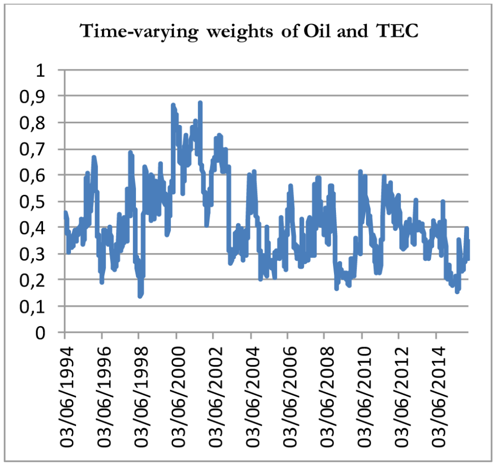
Notes: $W_{o,t}$ and $W_{s,t}$ are the optimal weights of oil and each sector equity where W_s=1– W_o. EAR is the effective annual rate of return while $\sigma_{p.a}$ is the annualized standard deviation. $\sigma_{o,s}$ is the conditional covariance between returns of oil and each sector. ER (p) and σ_p are expected returns and risk of sector/oil portfolio while H.R. is the hedge ratio.

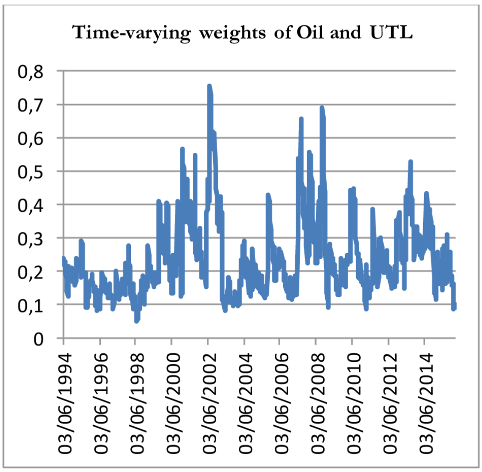
Figure 2 illustrates the graphical evolution of the optimal weights of oil for each of the sector/oil portfolios. It is evident that the weights are time-varying and even though the point estimates indicate the need to overweight investment in sector equity, there are times when overweighting investment in oil becomes necessary. The principal inference from Figure 2 is that portfolio and risk management are dynamic processes and portfolio managers and investors need to constantly monitor and rebalance their sector equity/oil portfolios to optimize risk-adjusted returns.

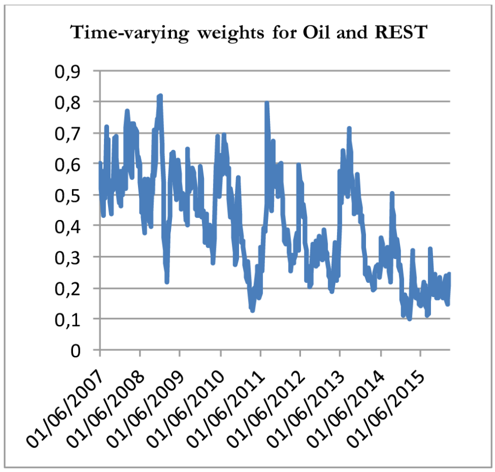
Figure 2: Time-varying capital allocation weights between each economic sector and oil

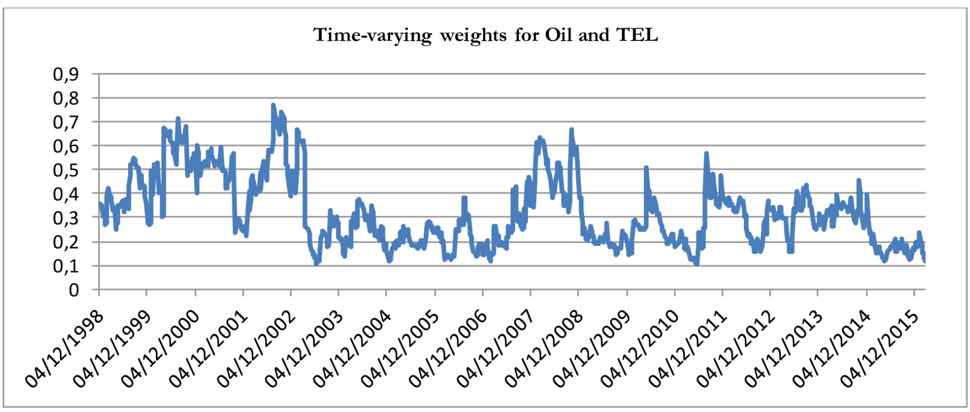



Time-varying weights of Oil and MAT
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
03/06/1…
03/06/2…


Time-varying weights of Oil and TEC
1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
03/06/1994
03/06/1996
03/06/1998
03/06/2000
03/06/2002
03/06/2004
03/06/2006
03/06/2008
03/06/2010
03/06/2012
03/06/2014


Time-varying weights of Oil and UTL
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
03/06/1994
03/06/1996
03/06/1998
03/06/2000
03/06/2002
03/06/2004
03/06/2006
03/06/2008
03/06/2010
03/06/2012
03/06/2014


Time-varying weights for Oil and REST
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
01/06/2007
01/06/2008
01/06/2009
01/06/2010
01/06/2011
01/06/2012
01/06/2013
01/06/2014
01/06/2015


Time-varying weights for Oil and TEL
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
04/12/1998
04/12/1999
04/12/2000
04/12/2001
04/12/2002
04/12/2003
04/12/2004
04/12/2005
04/12/2006
04/12/2007
04/12/2008
04/12/2009
04/12/2010
04/12/2011
04/12/2012
04/12/2013
04/12/2014
04/12/2015

We further examine the risk and returns of each sector/oil portfolio. We first annualize the sector and oil returns and risk (standard deviation). We then use the optimal weights $W_{o,t}$ and $W_{s,t}$ to compute the expected returns of the portfolio, *ER (p)*, as well as the standard deviation or risk of the portfolio σ_p. It is apparent that portfolio risk σ_p tends to significantly decline after adding oil in the sector equity portfolio. For example, adding oil (annualized standard deviation of 30.732) to REST and CSI (standard deviation of 29.682 and 14.277 respectively) results in reduced portfolio risk of 21.622 and 12.965. There are discernable disparities in *ER (p)* and σ_p, but when *ER (p)* is normalized with σ_p, we find that the CSI/oil (TEL/oil) portfolio offers the highest (lowest) return per unit of total risk. This is followed by the HCI/oil (REST/oil) portfolios. Our results further support the idea that each sector offers singular risk-return rewards. Our results can also be used to rank the sector/oil portfolios in terms of risk-adjusted returns.

Kroner and Sultan (1993) developed a model to assess the cost of hedging to achieve the minimum-variance portfolio. Specifically, the optimal hedge ratio (H.R) is derived as follows:

$$HR(s) = \frac{\sigma_{o,s}}{\sigma_o^2} \tag{11}$$

The HR indicates the cost of hedging \$1 long on a stock by going short on oil. The hedge ratio between oil and sector indices varies between –0.0738 in the REST/WTI portfolio to 0.0618 in the EGY/WTI portfolio. This suggests that an investor with a \$1 long (short) position in EGY (REST) sector indices can pay 6.18 (7.38) cents to hedge the position with a short (long) position in WTI futures. Similarly, for TEC (IND) sector indices, a \$1 long position can be hedged for 1.06 (0.14) cents with a short position in WTI oil futures. Therefore, the least expensive hedge is long (short) IND (TEL) and short (long) WTI oil while the most expensive hedge is long (short) EGY (REST) and short (long) WTI oil. The dominant inference from the evidence in Table 5a is that there is good hedging effectiveness (due to very low hedge ratios) involving oil and sector portfolios, suggesting that it is worth considering an addition of oil futures in a diversified portfolio of sector stocks to improve the risk-adjusted performance of the resultant sector/oil portfolio.

2. RISK PARITY APPROACH TO RISK MANAGEMENT

Unlike the traditional portfolio optimization approach, which focuses on the allocation of capital among different asset classes, the risk parity approach to portfolio management is premised on the allocation of risk. The risk parity approach is based on the idea of the adjustment of asset allocation through leveraging and deleveraging to the equal amount of risk (volatility) per asset can result in a higher Sharpe ratio relative to the traditional capital allocation approach. Under the risk parity approach, a minimum variance portfolio can be created when the contribution of each asset to the portfolio's aggregate volatility evens out. The attempt to achieve equal risk contribution by every asset class ensures that true diversification is achievable as risk parity portfolios become equally sensitive to exposure from every asset class. This state is particularly appealing since different economic settings present different risk exposures to the varied asset classes throughout the business cycle.

Since all assets should have an equal marginal contribution to the total risk of the portfolio, we first establish the marginal contribution of each asset to portfolios total risk. Generally, the upshot will be a significant allocation to lower risk asset while allocations to the higher risk assets will be below what the traditional portfolio optimization approach would typically make. We create an optimal risk parity portfolio by adjusting the weights of each asset (sector and oil futures) until the marginal contributions (MC) of the two asset classes are equal.

$$MC_1 = w_1 X \frac{\Delta \text{ in } \sigma_{\mathrm{p}}}{\Delta \text{ in } w_1} = w_1 X \left(\frac{w_1\ \sigma_1^2 + w_2\ Cov(R_1, R_2)}{\sigma_{\mathrm{p}}} \right)$$

$$MC_2 = w_2 X \frac{\Delta \text{ in } \sigma_{\mathrm{p}}}{\Delta \text{ in } w_2} = w_2 X \left(\frac{w_2\ \sigma_2^2 + w_1\ Cov(R_1, R_2)}{\sigma_{\mathrm{p}}} \right)$$

For a portfolio comprising two assets 1 and 2, w_1 and w_2 represent the proportion of wealth invested in asset 1 and asset 2 respectively while σ_1^2 and σ_2^2 refer to the variances of returns of asset1 and 2 respectively. $Cov\ (R_1, R_2)$ is the covariance between the returns of both assets.

We find variations in capital allocations between each sector and oil. For example, an investor can allocate 40% and 60% (19% and 81%) of his wealth in a portfolio comprising oil futures and real estate (oil futures and consumer staples) fund to improve risk-adjusted returns. According to marginal contribution to portfolio risk or volatility, real estate sector, REST, contributes about 70% to the total risk of a portfolio comprising REST and oil although only 60% of capital is allocated.

Table 5b: Risk parity portfolios

	Traditional Capital Allocations				Marginal contribution to portfolio risk				Risk parity weights	
	σ_S	W_O	W_S	σ_P	MC_O	MC_S	MCW_O	MCW_S	RPW_O	RPW_S
CDI	0.209	0.295	0.705	0.173	0.047	0.126	0.272	0.728	0.403	0.597
CSI	0.146	0.192	0.808	0.132	0.026	0.106	0.198	0.802	0.313	0.687
EGY	0.245	0.371	0.629	0.191	0.067	0.124	0.351	0.649	0.444	0.556
FIN	0.242	0.318	0.682	0.192	0.049	0.142	0.257	0.743	0.443	0.557
HCI	0.180	0.260	0.740	0.155	0.041	0.114	0.262	0.738	0.364	0.636
IND	0.202	0.294	0.706	0.169	0.048	0.121	0.283	0.717	0.394	0.606
MAT	0.230	0.351	0.649	0.184	0.063	0.121	0.341	0.659	0.427	0.573
TEL	0.276	0.412	0.588	0.206	0.077	0.129	0.375	0.625	0.475	0.525
UTL	0.172	0.234	0.766	0.150	0.034	0.115	0.228	0.772	0.352	0.648
REST	0.309	0.400	0.600	0.222	0.067	0.155	0.302	0.698	0.509	0.491
TEL	0.228	0.321	0.679	0.183	0.053	0.130	0.288	0.712	0.425	0.575
OIL	0.305									

Notes: σ_S is the annualized standard deviation of returns of each sector and WTI oil. W_S and W_O are the weights of capital allocations using the traditional portfolio approach and σ_P is the standard deviation of a portfolio comprising a sector fund and the oil futures. MC_O and MC_S (MCW_O and MCW_S) are the marginal contribution (marginal contribution weights) of oil and sector to the portfolio risk, σ_P. Lastly, RPW_O and RPW_S are the risk parity weights of oil and each sector which guarantee equal contribution of risk by each sector and oil to portfolio risk. These weights are derived using optimization software.

Similarly, while we allocate 68% of capital to FIN sector to form FIN/OIL portfolio, FIN sector contributes about 74% to total portfolio risk. Except for CSI-OIL and HCI-OIL portfolios, we find that each of the remaining eight sectors contributes a higher proportion to total portfolio risk than the proportion of wealth or capital allocated to each. The findings are consistent with lower allocations to an asset class with higher risk (OIL in our case whose annualized standard deviation of 0.305 is higher than annualized standard deviation of every sector).

We construct risk parity portfolios and identify the optimal weights which would result in an equal contribution to total portfolio risk by each asset class. While capital allocations were optimally determined to be 40%/60% (19%/81%) for OIL /REST (OIL/CSI) portfolio, we would require, under risk parity portfolio, 51%/49% (31%/69%) contributions to portfolio risk for the contributions of each asset class to even out. This is particularly important if sector funds and oil futures exhibit different risk exposures in different economic cycles. The risk allocations and subsequent adjustments would assist in better risk diversification while improving our Sharpe ratio. We find significant differences between the capital allocation weights and the risk parity portfolio weights.

VI. ROBUSTNESS CHECKS

U.S. economic sectors are susceptible to disruptive structural shifts occasioned by either major domestic or global financial, economic, or political events. Therefore, it is possible that our evidence and inferences so far may have been contaminated by a potential occurrence of structural shifts in returns. We investigate this possibility using the sequential multiple structural break test developed by Bai and Perron (1998, 2003). The methodology is premised on the following hypotheses: Ho: There are N_B breaks, and Ha: There are N_B *+1* breaks. We restrict N_B to 5 and also impose a 15% trimming value. We perform the sequential supF_T $(B+1 \mid B)$ structural change test and generate the corresponding F-statistic to identify the number of breaks. We complement our test by minimizing the Bayesian Information Criterion (BIC). The BIC break identification method allows for a penalty factor as the dimensions of the model increases.

The results presented in Table 6 reveal that six sectors, namely Consumer Staple (CSI), Financial (FIN), Healthcare (HCI), Technology (TEC), Real Estate (REST), and Telecommunication (TEL), experienced structural breaks. The sequential F-statistics are statistically significant rejecting the null hypothesis of zero. The Technology (TEC) sector has two breaks, hence the null hypothesis of zero (one) break is rejected at the 5% significance level in favor of one (two) breaks. We suggest possible causes of the structural shifts or breaks in sector returns. The structural breakpoints or dates, (T_{bi}), show that three sectors Consumer Staple (CSI), Financial (FIN), and Healthcare (HCI) experienced breaks during 1998. These breaks could have been occasioned by the collapse of Long-Term Capital Management (LTCM), the 1997/1998 Asian crisis, or the sovereign debt default by Russia and the subsequent Ruble crisis. The Technology (TEC) sector had a break in March 2000, a period that corresponds with the Dot-com bubble bursting. The breaks in the Telecommunication (TEL) and Technology (TEC) sectors in 2002 and 2003 certainly originated from the shocks of the 2001 economic recession and the stock market crash of October 2002. The break in the Real Estate (REST) sector clearly originated from the 2007-2008 housing market meltdown and the resulting global financial crisis.

After identifying the break dates and number of breaks, we establish the number of regimes or partitions created by the breaks. The Bai and Perron (1998, 2003) test generates the mean returns $\hat{c}$ of each regime.

Table 6: Test for Structural Breaks

Sector	Tbi	F-Stat	Mean	Regime 1	Regime 2	Regime 3
CSI	4/3/1998	**10.408		6/03/1994 – 3/27/1998	4/03/1998 – 2/26/2016	
			$\hat{c}$	***0.5225	**0.1335	
FIN	4/17/1998	**9.195		6/03/1994 – 4/10/1998	4/17/1998 – 2/26/2016	
			$\hat{c}$	***0.5794	***0.0457	
HCI	7/17/1998	**8.857		6/03/1994 – 7/10/1998	7/17/1998 – 2/26/2016	
			$\hat{c}$	***0.5719	*0.1354	
REST	3/6/2009	**13.990		6/01/2007 – 2/27/2009	3/06/2009 – 2/26/2016	
			$\hat{c}$	***-1.3504	**0.4226	
TEC	3/24/2000	**10.469		6/03/1994 – 3/17/2000	3/24/2000 – 6/20/2003	6/27/2003 – 2/26/2016
	6/27/2003	**10.197	$\hat{c}$	***0.7719	***-0.8203	***0.1678
TEL	9/27/2002	**11.333		12/04/1998 – 9/20/2002	9/27/2002 – 2/26/2016	
			$\hat{c}$	***-0.6078	*0.2194	

Notes: The critical value F-statistic at the 5% significance level is 8.58.

Using the results obtained in Table 6, we follow a two-step process proposed by Choi et al. (2010). First, we estimate the mean return for each regime, ĉ. Second, we derive the break-adjusted returns, $R_t^* = R_t - \hat{c}$ where R_t is the continuously compounded sector return at period t equal to the natural log difference of the sector indices. This is comparable to removing the mean of every regime from R_t to spawn a similar mean return across the entire sample. This approach circumvents the loss of degrees of freedom. We use the break-adjusted returns and replicate the results of Table 4 using the EDCC-GARCH model.

Table 7: EDCC-GARCH estimates using break-adjusted returns

		a_1	a_2	A_{11}	A_{21}	A_{12}	A_{22}	B_{11}	B_{21}	B_{12}	B_{22}	α	β
CSI	Est.	0.003	0.004	***0.150	0.013	0.006	0.068	***0.749	***0.148	0.019	***0.901	0.000	*0.865
	std. err	0.085	0.044	0.015	0.066	0.017	0.128	0.189	0.022	0.314	0.051	0.032	0.501
	t-stat	0.036	0.097	9.954	0.193	0.387	0.535	3.952	6.690	0.061	17.589	0.000	1.726
FIN	Est.	0.096	***1.045	***0.156	***0.098	0.001	0.095	***0.815	0.002	0.012	***0.794	0.000	***0.960
	std. err	0.123	0.365	0.007	0.039	0.019	0.473	0.071	0.034	0.093	0.082	0.017	0.213
	t-stat	0.784	2.863	22.908	2.534	0.048	0.200	11.465	0.048	0.131	9.650	0.000	4.518
HCI	Est.	0.159	***0.852	***0.139	0.125	0.019	0.087	***0.721	***0.217	0.021	***0.751	0.000	***0.967
	std. err	0.180	0.051	0.017	0.131	0.049	0.576	0.203	0.035	0.632	0.213	0.018	0.285
	t-stat	0.883	16.787	8.012	0.953	0.388	0.151	3.548	6.150	0.033	3.525	0.000	3.393
TEC	Est.	0.126	0.018	***0.107	0.037	0.005	0.082	***0.855	**0.044	0.018	***0.896	0.000	**0.973
	std. err	0.098	0.024	0.010	0.035	0.018	0.096	0.027	0.021	0.046	0.033	0.011	0.471
	t-stat	1.287	0.725	11.086	1.039	0.284	0.857	31.470	2.095	0.390	27.502	0.000	2.065
RES	Est.	0.133	***0.240	***0.290	**0.012	0.000	0.119	***0.625	**0.048	0.066	***0.832	0.000	**0.868
	std. err	0.324	0.084	0.011	0.005	0.036	0.198	0.075	0.024	0.113	0.080	0.037	0.420
	t-stat	0.409	2.864	26.073	2.231	0.013	0.601	8.358	1.992	0.585	10.443	0.000	2.070
TEL	Est.	0.122	***0.481	***0.121	*0.082	0.006	0.061	***0.857	0.000	0.001	***0.873	0.000	***0.992
	std. err	0.084	0.046	0.010	0.045	0.021	0.226	0.046	0.025	0.088	0.057	0.008	0.097
	t-stat	1.451	10.518	12.420	1.822	0.267	0.272	18.656	0.001	0.007	15.366	0.000	10.233

Notes: Est. is the estimated coefficient while std. err is the standard error for the economic sectors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively

The EDCC-GARCH model results for the sectors that encountered structural breaks are gathered in Table 7. For the six sectors and oil market, the own past shocks and the own lagged volatility remain the main propagators of current conditional volatility since shock parameters A_{11} and A_{22} and volatility parameters B_{11} and B_{22} remain statistically and economically significant. Moreover, we still find that there are no shocks and volatility transmissions from each sector to the oil market since parameters B_{12} and A_{12} are not significantly different from zero, which is similar to evidence presented in Table 4. Further, we find that the shock parameter A_{21} for CSI (FIN) becomes (remains) insignificant (significant) when break-adjusted returns are used in the EDCC-GARCH model. For the remaining four sectors Healthcare (HCI), Technology (TEC), Real Estate (REST), and Telecommunication (TEL), the shock and volatility transmission parameters decrease in statistical and economic significance, implying the parameters of these sectors reported in Table 4 are overestimated.

Table 8: Fitness of the EDCC model relative to DCC model

Portfolio	LL(DCC)	LL(EDCC)	LR
CDI/OIL	– 4658.46	– 4637.23	***42.466
CSI/OIL	– 4996.63	– 4981.86	***29.546
EGY/OIL	– 4428.05	– 4404.61	***46.864
FIN/OIL	– 4583.10	– 4552.47	***61.258
HCI/OIL	– 4778.49	– 4765.66	***25.658
IND/OIL	– 4653.04	– 4636.34	***33.392
MAT/OIL	– 4496.72	– 4455.64	***82.160
TEC/OIL	– 4330.56	– 4318.08	***24.952
UTL/OIL	– 4850.28	– 4838.29	***23.962
REST/OIL	– 2120.00	– 2112.88	***14.242
TEL/OIL	– 3619.86	– 3608.16	***23.400

Notes: LL (DCC) and LL (EDCC) are the log likelihood of the DCC and extended DCC models. LR is the likelihood ratio computed as 2*[(LL (EDCC)–(LL (DCC)] where EDCC is the unrestricted (full) model while the DCC is the restricted (diagonal) model.

Therefore, structural breaks can contaminate the evidence through upward biased parameters or misidentification of whether it is the oil price shock of oil or return volatility that truly induces conditional volatility in sector returns. Lastly, we investigate whether the EDCC model performs better than the DCC model. To this end, we perform the likelihood ratio (LR) test by estimating the DCC and EDCC models and then comparing the fit of both models. The resulting LR statistic has chi-square distribution with four degrees of freedom equal to A_{12}, A_{21}, B_{12} and B_{21} parameters that are constrained to zero in the DCC model. Results in table 8 indicate that the unconstrained EDCC model fits significantly better than the DCC model since the LR is significant at 1%.

VII. CONCLUSIONS AND POLICY IMPLICATIONS

This study investigates volatility and shock interactions between each U.S. sector equity index and the oil market using the newly developed EDCC-GARCH model. Unlike the conventional DCC-GARCH model, the EDCC-GARCH can capture volatility and shock interactions between markets as well as estimate the time-varying conditional correlations. We conduct a number of misspecification tests. Our study reveals that (i) the correlation between the sector volatility and the oil return volatility is not time-invariant as has been assumed in previous studies; (ii) there is causality of variance between each sector and oil market as evidenced by three different causality-in-variance tests; (iii) there is either volatility or shock transmission from oil to each sector but not the reverse. This confirms that there is information flow between oil and sector equity markets. Further, it may be necessary to incorporate oil in the pricing of sector-based equity instruments; (iv) investors can minimize and hedge risk by allocating a portion of their wealth to an oil commodity and adding it to a well-diversified portfolio of sector stocks (such as sector ETFs and mutual funds) to form a sector/oil portfolio. The cost of hedging is low and may require going long in some sectors and going short in others to improve risk-adjusted returns of a sector-oil portfolio. This evidence conflicts with the results of Anoruo and Mustafa (2007), who found no diversification benefit of holding assets in oil and stock markets, and Filis, et al. (2011), who found that investing in the oil market cannot protect from losses in the stock market. Our results also show that the conditional correlation between each economic sector and the oil market is low, time-varying, and slowly decaying. The slow decay implies that correlations can be predicted from past patterns as they tend to persist, which is an observation that contradicts the efficient market hypothesis; (v) to improve the performance of sector/oil portfolios; an investor needs to overweight his or her investment in sector equity. This is particularly important given that shocks or conditional volatility (or both) from oil markets are likely to magnify conditional volatility of sector returns; and lastly, (vi) there is a need to account for structural breaks to skirt upward bias in the estimation of shock and volatility spillover parameters. Our findings reflect the diversification potential that oil commodities offer to U.S. investors holding sector portfolios such as sector ETFs and mutual funds.

This study can be extended to sector and oil markets of other countries or to oil and other financial assets.

VIII. REFERENCES

Amado, C., Teräsvirta, T., 2014. Conditional correlation models of autoregressive conditional heteroscedasticity with nonstationary GARCH equations. Journal of Business & Economic Statistics. 32, 69-87. doi:10.1080/07350015.2013.847376

Anoruo, E., Mustafa, M., 2007. An Empirical Investigation into the Relation of Oil to Stock Market Prices. North American Journal of Finance and Banking Research. 1, 22-36.

Apergis, N., Miller, S. M., 2009. Do structural oil-market shocks affect stock prices?. Energy Economics, 31, 569-575. doi:10.1016/j.eneco.2009.03.001.

Arouri, M. E. H, Fouquau, J., 2009. On the short-term influence of oil price changes on stock markets in GCC countries: linear and nonlinear analyses. Economics Bulletin. 29, 806-815.

Arouri, M. E. H., Jouini, J., Nguyen, D. K., 2011. Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International Money and Finance, 30, 1387-1405. doi:10.1016/j.jimonfin.2011.07.008.

Arouri, M. E. H., Lahiani, A., Nguyen, D. K., 2011. Return and volatility transmission between world oil prices and stock markets of the GCC countries. Ec onomic Modelling, 28, 1815-1825. doi:10.1016/j.econmod.2011.03.012.

Arouri, M. E. H., Nguyen, D. K., 2010. Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. Energy Policy, 38, 4528-4539. doi:10.1016/j.enpol.2010.04.007.

Asness, C. S., Frazzini, A., Pedersen, L. H., 2012. Leverage Aversion and Risk Parity. Financial Analysts Journal. 68, 47-59.

Bai, J., Perron, P., 1998. Estimating and Testing Linear Models with Multiple Structural Changes. Econometrica, 66, 47-78. doi:10.2307/2998540

Bai, J., Perron, P., 2003. Critical values for multiple structural change tests. The Econometrics Journal, 6, 72-78. doi:10.1111/1368-423x.00102.

Basher, S. A., Sadorsky, P., 2006. Oil price risk and emerging stock markets. Global Finance Journal, 17, 224-251.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. The Review of Economics and Statistics, 498-505.

Choi, K., Yu, W. C., Zivot, E. (2010). Long memory versus structural breaks in modeling and Forecasting realized volatility. Journal of International Money and Finance, 29, 857-875. *http://dx.doi.org/10.1016/j.jimonfin.2009.12.001*

Daly, K. J., Fayyad, A., 2011. Can oil prices predict stock market returns?. Modern Applied Science, 5, 44. doi:10.5539/mas.v5n6p44.

Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20, 339-350.

Engle, R.F., Sheppard, K., 2001. Theoretical and empirical properties of Dynamic Conditional Correlation Multivariate GARCH. NBER Working Paper 8554, National Bureau of Economic Research. doi:10.3386/w8554

Faff, R. W., Brailsford, T. J., 1999. Oil price risk and the Australian stock market. Journal of Energy Finance & Development, 4, 69-87. doi:10.1016/s1085-7443(99)00005-8.

Filis, G., Degiannakis, S., Floros, C., 2011. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 20, 152-164. doi:10.1016/j.irfa.2011.02.014.

Ghosh, S., Kanjilal, K., 2016. Co-movement of international crude oil price and Indian Stock Market: evidences from Nonlinear Cointegration Tests. Energy Economics, 53, 111-117. doi:10.1016/j.eneco.2014.11.002.

Hafner, C.M., Herwartz, H., 2006. A lagrange multiplier test for causality in variance. Economics Letters, 93, 137-141.

Hamilton, J. D., 1996. This is what happened to oil price-macro-economy relationship. Journal of Monetary Economics, 38, 215-220. doi:10.1016/s0304-3932(96)01282-2.

Hammoudeh, S., Choi, K., 2006. Behavior of GCC stock markets and impacts of US oil and financial markets. Research in International Business and Finance, 20, 22-44. doi:10.1016/j.ribaf.2005.05.008.

Jawadi, F., Arouri, M. E. H., Bellalah, M., 2010. Nonlinear linkages between oil and stock markets in developed and emerging countries. International Journal of Business, 15, 19-31.

Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. stock market,”. International Economic Review, 50, 1267-1287. doi:10.1111/j.1468-2354.2009.00568.x.

Kroner, K. F., Ng, V. K., 1998. Modeling asymmetric comovements of asset returns. Review of Financial Studies, 11, 817-844. doi:10.1093/rfs/11.4.817.

Kroner, K. F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. Journal of Financial and Quantitative Analysis, 28, 535-551.

Ling, S., Mcaleer, M., 2003. Asymptotic theory for a vector ARMA-GARCH model. Econometric Theory, 19, 280-310. doi:10.1017/s0266466603192092.

Malik, F., Hammoudeh, S., 2007. Shock and volatility transmission in the oil, US and Gulf equity markets. International Review of Economics & Finance, 16, 357-368. doi:10.1016/j.iref.2005.05.005.

Malik, F., Ewing, B. T., 2009. Volatility transmission between oil prices and equity sector returns. International Review of Financial Analysis, 18, 95-100. doi:10.1016/j.irfa.2009.03.003.

Mensi, W., Beljid, M., Boubaker, A., Managi, S., 2013. Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. Economic Modelling, 32, 15-22. doi:10.1016/j.econmod.2013.01.023.

Miller, J. I., Ratti, R. A., 2009. Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics, 31, 559-568. doi:10.1016/j.eneco.2009.01.009.

Nakatani, T., Teräsvirta, T., 2008a. Appendix to testing for volatility interactions in the Constant Conditional Correlation GARCH Model. Department of Economic Statistics, Stockholm School of Economics, available at *http://swopec.hhs.se/hastef/abs/hastef0649.htm*.

Nakatani, T., Teräsvirta, T., 2008b. Positivity constraints on the conditional variances in the family of conditional correlation GARCH models. Finance Research Letters, 5, 88-95. doi:10.1016/j.frl.2008.02.001.

Nakatani, T., Teräsvirta, T., 2009. Testing for volatility interactions in the Constant Conditional Correlation GARCH model. The Econometrics Journal, 12, 147-163. doi:10.1111/j.1368-423x.2008.00261.x.

Park, J., Ratti, R. A., 2008. Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30, 2587-2608.

Ready, R.C., 2014. Oil Prices and the Stock Market. Available at SSRN: *https://ssrn.com/abstract=2140034* or *http://dx.doi.org/10.2139/ssrn.2140034*

Ross, S.A., 1989. Information and Volatility: The No-Arbitrage Martingale Approach to timing and Resolution Irrelevancy. The Journal of Finance, 44, 1-17. doi:10.1111/j.1540-6261.1989.tb02401.x.

Shadat, W., Orme, C., 2016. Robust parametric tests of constant conditional correlation in a MGARCH model. Econometric Reviews, 1-26. doi:10.1080/07474938.2015.1122120.

Sukcharoen, K., Zohrabyan, T., Leatham, D., Wu, X., 2014. Interdependence of oil prices and stock market indices: A Copula approach. Energy Economics, 44, 331-339. doi:10.1016/j.eneco.2014.04.012.

Tauchen, G.E., Pitts, M., 1983. The price variability-volume relationship on speculative

Markets. Econometrica, 51, 485-505. doi:10.2307/1912002.

Tse, Y. K., 2000. A test for constant correlations in a multivariate GARCH model. Journal of econometrics, 98, 107-127. doi:10.1016/s0304-4076(99)00080-9.

Vivian, A., Wohar, M. E., 2012. Commodity volatility breaks. Journal of International Financial Markets, Institutions and Money, 22, 395-422. doi:10.1016/j.intfin.2011.12.003.

Yu, L., Wang, S., Lai, K. K., 2008. Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy Economics, 30, 2623-2635. doi:10.1016/j.eneco.2008.05.003.