Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies

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Abstract

This study explores the time patterns of volatility spillovers between energy market and stock prices of seven major global financial markets including clean energy, energy, information technology corporations, equity markets and United States economic policy index over the period vary from December 28, 2000 to December 31, 2018. We employ a time domain connectedness measures of Diebold and Yilmaz (DY, 2009, 2012 and 2014) to examine spillover mechanism of volatility shocks across future markets. Optimal weights and hedge ratios are calculated for portfolio diversification and risk management. The main findings of the study conclude that oil shocks are exogenous and contribution of oil market volatility to global financial markets is insignificant. The returns of World Stock Index and World Energy Index are major transmitters of volatility to clean energy market. Moreover, the impact of energy market become strong in global financial market when data is divided into pre, during and post financial crisis periods. Finally, the hedge ratios are volatile over time and their maximum value is observed during the financial crisis period of 2008-09. The optimal portfolio between energy and stock prices are heavily weighted to the stock markets.

JEL classification: C58; G11; Q43

Keywords: Clean energy; Traditional energy; Technology stocks; Dynamic return spillovers, Optimal hedge ratios, Portfolio diversification

1. Introduction

Over the last few decades, the world energy consumption has increased substantially leading to unprecedented levels of CO_2 emissions and global warming that impose great threats to ecosystem and global environment. As a result, there has been growing environmental concerns and requests for more sustainable energy resources due to issues of climate change and adverse impact of intensive carbon emissions from conventional energy sector as well as increasing cost of fossil fuels. Since then, clean energy sector has gained a lot of attention from both investors and policymakers. According to Bloomberg NEF (New Energy Finance) report, investment in Global clean energy sector has reached $332.1 billion in 2018. Over the last five years, clean energy investment continues to exceed $300 billion a year and it is expected that market capitalization of the sustainable energy sector to reach more than $2 trillion over the next few years.

Given the rapid expansion in demand for and investment in clean energy sector, it's of high importance to investors and policymakers to understand the dynamic interconnectedness as well as the volatility transmission mechanisms between clean energy prices, conventional energy prices and other financial markets. However, literature on the relationship between oil prices and the stock prices of clean energy and conventional energy is not clear (Kumar et al., 2012, Maghyereh et al., 2019). Furthermore, empirical studies on relationship between crude oil prices and stock prices of clean energy and technology companies are very rare and provide inconclusive results (Ahmad, 2017, Bondia et al., 2016, Henriques and Sadorsky, 2008, Kumar et al., 2012, Maghyereh et al., 2019, Sadorsky, 2012).

To fill this gap in the literature, this study aims at investigating the dynamic connectedness and volatility transmission channels between oil prices and stock prices of clean energy, traditional energy, technology companies and other financial assets using the data from December 28, 2000 to December 31, 2018. The spillover index approach by Diebold and Yilmaz (2009, 2012, 2014) is employed to identify the transmission mechanism of volatility shocks between oil market and global financial markets. This approach can assess the magnitude and direction of connectedness across financial variables over time and hence it provides an alternative way to check the contagion effect across global future markets. Recently, this approach has been widely utilized to examine the connectedness network across different assets (Zhang et al., 2017; Maghyereh et al. 2019), institutions (Diebold and Yilmaz, 2014; 2016) and markets (Shehzad et al. 2017; Ahmed and

Elsayed, 2018; Wang and Wu, 2018; Elsayed and Yarovaya, 2019). Nevertheless, a few studies have explored the dynamic connectedness across global financial markets while accounting for recent financial crisis. In this context, the current study analyzes the dynamic connectedness to understand the transmission of volatility spillover between oil and global financial markets by incorporating the effect of recent financial crisis.

In doing so, our paper contributes to the literature in several ways. Firstly, previous literature examined the relationship and interdependence between oil prices, conventional energy and non-conventional energy stock indices and ignored the fact that dynamic interconnectedness among those markets is affected by volatility and performance of other financial markets as well as level of macroeconomic uncertainty (see for example; Ahmad, 2017, Managi and Okimoto, 2013, Reboredo et al., 2017, Reboredo and Ugolini, 2018, Wen et al., 2014, among others). Therefore, we extend the analysis by including stock prices of global financial markets such as World Stock Price Index, World Commodity Price Index, IT Industry Price Index, US Treasury Benchmark Bond 10 Years. In addition, WTI crude oil price, VIX index and US Economic Policy Uncertainty Index are included in order to control for the degree of macroeconomic uncertainty and global financial risk. This contribution is very important for economic agents since understanding volatility interlinkages and transmission mechanisms is very crucial for accurate valuation and pricing of financial instruments and financial derivatives.

Secondly, to examine information transmission mechanisms and direction of spillovers between markets, this study utilizes the spillover approach proposed by Diebold and Yilmaz (2009, 2012, 2014) based on forecast-error variance decomposition matrix from a Generalised Vector Autoregressive Model. This approach provides accurate information on the direction and intensity of risk spillover to investors, thus, supporting in price asset allocation and investment decisions. Thirdly, we analyze a rolling window approach to detect the time-varying dynamics of the spillover index and observe how the recent financial crisis affected the intensity and directional spillover between oil and financial markets. The rolling window approach allows us to examine the risk spillover over time without having to use a cutoff date to create sub-samples. Fourthly, our dataset includes daily time-series data on stock prices of clean energy, traditional energy, technology companies and other financial assets over the period 2000 to 2018. Our sample period allows us to compare their evolution among three different sub-periods (i) pre (ii) during and (iii) post financial crisis period. Finally, like previous studies, such as Arouri et al. (2012); Sadorsky (2012) and Antonakakis et al. (2018) we have provided extensive analysis of hedging and portfolio diversification strategies between renewable energy, conventional energy, technology sector, and other financial markets. Understanding the direction of cross-market spillovers and its dynamic behaviors allow investors to mitigate the risk and choose the optimal asset allocation strategy that minimizers potential risk during period of high stress and uncertainty.

The empirical results of Diebold and Yilmaz (DY, 2009, 2012 and 2014) suggest that energy market is highly affected by the shocks from global financial market. In addition, we find that stock returns of WilderHill Clean Energy Price Index (CEPI), MSCI World Energy Price Index (WEPI), MSCI World IT Price Index (WIPI), MSCI World Stock Price Index (WSPI), MSCI World Commodity Producers Index (WCPI), VIX index (VIX), US Economic Policy Uncertainty Index (USEPU) exert the highest impact on energy market. However, the results are somewhat different, when data is divided into pre-during and post financial crisis period. Finally, the evidence supports that hedge ratios are volatile and reach their maximum value during the financial crisis period of 2008-09. The optimal portfolio between energy and stock prices are heavily weighted to the stock markets.

The rest of the paper is organized as follows. In section 2, we review previous empirical studies on relationship and spillovers between conventional, non-conventional, and other financial markets. Section 3 outlines the econometric approach and presents preliminary statistics of our dataset. Section 4 discusses empirical results of the spillover approach and analysis of hedging and portfolio diversification strategies. Finally, section 5 summarizes our results and provides concluding remarks.

2. Literature Review

Literature review on dynamics of volatility spillovers and risk transmission between oil, energy stock prices and other financial markets could be divided in two main streams. Firstly, empirical studies examined the link and association between oil, clean energy and conventional energy prices. Secondly, papers investigated volatility transmission between clean energy stock prices, oil prices, and technology stock prices.

Literature on the relationship between oil prices and the stock prices of clean energy and conventional energy is not clear (Kumar et al., 2012, Maghyereh et al., 2019). For instance, Broadstock et al. (2012), using weekly data for China over the period January 7, 2000 to May 27, 2011and time-varying conditional correlation approach, examined dynamic association between oil prices and energy stock prices. Results show that oil price fluctuations have a significant impact on new energy stock prices. In particular, volatility transmission and dependence between oil prices and new energy stock prices notably increased after the global financial crisis in 2008. Along the same vein, Wen et al. (2014) examined return and volatility spillover transmission between stock prices of clean energy and fossil fuel companies in the Chinese financial market using the asymmetric BEKK approach. Findings indicated significant and asymmetric spillovers between clean energy and fossil fuel companies over the sample period. Furthermore, clean energy and fossil fuel stocks are competing assets where investment in clean energy stocks are tend to be riskier than fossil fuel stock.

Likewise, Managi and Okimoto (2013) investigated dynamic interconnectedness between oil prices and clean energy prices based on Markov-Switching Vector Autoregressive (MSVAR) approach that endogenously account for structural breaks. Their results indicated a strong and positive association among oil prices and clean energy stock prices following the structural break of oil prices in late 2007.

Later, Reboredo et al. (2017) examined dynamic interdependence and causality directions between traditional and non-traditional energy using wavelets analysis as well as linear and non-linear Granger causality tests at different time scales. To this end, they used data for daily spot prices for WTI crude oil and different renewable energy stock indices over the period January 2006 to March 2015. Empirical results revealed a weak dynamic relationship between oil and clean energy indices in the short run that becomes stronger gradually towards the long run. In addition, Granger causality results show no linear causality at higher frequencies but mixed results of unidirectional and bidirectional causality relationship depending on the time horizon in short run. Furthermore, their analysis provided evidence against non-linear causality at different time scales and frequencies. In a more recent paper, Reboredo and Ugolini (2018) examine dynamic volatility spillovers between clean energy stock prices and different energy prices (oil, gas, electricity and coal) taking into account direct and indirect transmission channels using vine copula models based on data for the European Union and the U.S. over the period January 2009 to September 2016. Findings show that prices of oil and electricity are key determinants of conditional dependence in EU and U.S. markets. Oil is the major contributor of spillover to clean energy stock returns in the U. S. while, electricity is the main transmitter of volatility to clean energy stock returns in the European Union. In addition, they find no evidences of asymmetric impact of energy prices on clean energy prices.

Another strand of the literature focuses on studying volatility transmission between oil prices, clean energy stock prices, and technology stock prices. According to the literature, there is a positive relationship between prices of crude oil and prices of clean energy due to substitution effects. As oil price increases and oil becomes more expensive, this would encourage economic agents to substitute clean energy for conventional energy, which in turns increases the demand for technology and hence the stock prices of technology companies since clean energy companies depend heavily on inputs from technology companies (Ahmad, 2017, Kumar et al., 2012, Managi and Okimoto, 2013).

Although previous studies examined in detailed the volatility transmission between oil conventional energy and financial markets, the association and risk transmission between oil prices, clean energy and technology stock prices remain extremely under studied (Maghyereh et al., 2019). Indeed, this is particularly surprising given the increased demand for and investment in clean energy sector.

One of the early papers in this area presented by Henriques and Sadorsky (2008) who study relationship between oil prices changes, clean energy stock prices, technology stock prices, and interest rates using Vector Autoregression (VAR) model and weekly data over the period January 3, 2001, to May 30, 2007. On the one hand, they reported a significant impact of technology shocks on alternative energy companies compared with oil price shocks. On the other hand, technology stock prices are influenced by changes in oil prices. Similar results are obtained by Sadorsky (2012), who analyse the dynamic correlation and risk transmission between oil prices and stock prices of clean energy and technological companies using several multivariate GARCH models, namely BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation. They argued that stock prices of clean energy are highly correlated with stock prices of technology companies compared with oil prices. On contrary, Kumar et al. (2012) using a Vector

Autoregression (VAR) approach, reported a positive relationship between oil prices and stock prices of clean energy companies.

Using non-linear cointegration approach and Granger causality tests, Bondia et al. (2016) analyses the relationship between crude oil prices and the stock prices of clean energy and technology companies. They showed that stock prices of clean energy companies are influenced by oil prices and stock prices of technology companies in the short-run only. In addition, neither oil prices nor stock prices of technology companies' granger cause stock prices of clean energy in the long run. In a similar study, Ahmad (2017) examines dynamic connectedness between crude oil prices and stock prices of technology and clean energy companies using daily data over the period from May 2005 to April 2015. Results indicate that prices of technology stocks are key determinants of return and volatility spillovers of both clean energy stocks as well as crude oil prices. Furthermore, technology and clean energy stock prices are net transmitter of return and volatility spillovers to the crude oil (WTI) prices. In stark contrast, Maghyereh et al. (2019) examines returns and risk transmission between crude oil prices, clean energy stock prices and clean energy technology market at different time scales using wavelets multi time-scale with multivariate GARCH model and data span from January 1, 2001 to February 23, 2018. They found significant return spillovers from oil to clean energy and clean energy technology that is strengthen over time. Furthermore, there is a strong mutual association between clean energy and clean energy technology stocks at all-time horizons.

As can be seen, literature on relationship between crude oil prices and stock prices of clean energy and technology companies are inconclusive. Furthermore, previous studies ignored the fact that dynamic association between conventional and non-conventional energy stock indices could be driven by volatility and performance of other financial markets as well as macroeconomic uncertainty and global risk. As such, this study contributes to the existing literature by investigating the volatility spillover and risk transmission between conventional energy, non-conventional energy, and technology sector taking into account interconnectedness with other financial markets as well as impact of macroeconomic uncertainty and global financial risk.

3. Methodology

3.1. Econometric Method

Multivariate time-series methodology proposed by Diebold and Yilmez (2009, 2012, 2014 and 2015) is used in this paper to access the degree of connectedness between energy markets and financial markets. Diebold and Yilmez (2009) introduced a simple measure of connectedness that explicitly takes into account the interdependence of financial markets. Due to its simplicity, this method is widely used to measure spillover effects in global financial markets. This technique is based on VAR and known as variance decomposition procedure. The variance decomposition method splits the forecast error variance of the market *i* into parts attributed to the various markets included in the system. This way the impact of market shocks can be analyzed by studying the variance decompositions as it provides the flexibility to further break down the H-Step ahead of forecast errors into portions attributable to different shocks (Pesaran, et al., 2004). This also helps in controlling the overall fit of the model (in our case it is the degree of connectedness).

Consider the following jth order, N variable VAR model of the form:

$$z_t = \sum_{j=1}^{J} \theta_j z_{t-j} + \omega_t \qquad (1)$$

Where $z_t = (z_{1t}, z_{2t}, ..., z_{Nt})$ is a vector of variables at time t, θ_j , $j = 1,....., J$ are $N \times N$ parameter matrices and $\mu_t \sim N(0, \Sigma)$ is a vector of independently distributed error terms.

Moving average representation of Eq. (1) is as follows $z_t = \sum_{k=0}^{\infty} A_k \omega_{t-k}$ where $A_k = \Sigma \theta_k A_{j-k}$. Further, total, directional and net spillover indices are calculated from the generalized forecast error variance decomposition of the moving average representation of VAR model. The forecast error variance decomposition needs orthogonal innovations and shocks. Diebold and Yilmez (2012) have implemented the framework proposed by Pesaran and Shin (1998). This framework is based on generalized VAR (GVAR) methodology and does not require orthogonalization of shocks and invariant to the ordering of variable in the VAR (Chan-Lau, 2017). As the shocks to each variable are not orthogonalized, the sum of contribution to the variance of the forecast error is not necessarily equal to one (Diebold and Yilmez, 2012). The Diebold and Yilmez (2014 and 2015) method used in our analysis has several advantages over other methods. First, the method does not depend on the Cholesky factor identification of VAR and therefore, the results of variance decomposition do not hinge on the sequence of variables. Thus, the H-step ahead forecast error variance decomposition using the GVAR framework is defined as follows:

$$\lambda_{il}(H) = \frac{\sigma_{ll}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_l \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i \right)} \tag{2}$$

Where Σ is the variance matrix of the vector of errors ω, and σ_{ll} is the standard deviation of the error term of the j th equation. Finally, e_i is a selection vector with a value of one for the i th element, and zero otherwise. The spillover index yields a $N \times N$ matrix $\theta(H) = \left[\theta_{il}(H) \right]$, where each entry gives the contribution of variable j to the forecast error variance of variable i. Own-variable and cross-variable contributions are contained in the main diagonal and the off-diagonal elements of $\theta(H)$ matrix, respectively.

Because the own- and cross-variable variance contribution shares do not sum to one under the generalized decomposition (i.e., $\sum_{l=1}^{n} \theta_{il}(H) \neq 1$), each entry of the variance decomposition matrix is normalized by its row sum as follows:

$$\tilde{\varphi}_{il}(H) = \frac{\varphi_{il}(H)}{\sum_{l=1}^{n} \varphi_{il}(H)}, \tag{3}$$

With $\sum_{l=1}^{N} \tilde{\varphi}_{il}(H) = 1$ and $\sum_{i,l=1}^{N} \tilde{\varphi}_{il}(H) = n$ by construction.

This allows us to calculate total spillover index as:

$$Tsp(H) = \frac{\sum_{i,l=1,i\neq l}^{n} \tilde{\varphi}_{il}(H)}{\sum_{i,l=1}^{n} \tilde{\varphi}(H)} \times 100 = \frac{\sum_{i,l=1,i\neq l}^{n} \tilde{\varphi}_{il}(H)}{n} \times 100. \tag{4}$$

This index measures the total transmission of shocks across all markets and assets i.e., the ratio of the sum of all off-diagonal elements in the forecast-error variance decomposition matrix to the sum of all (both off-diagonal and diagonal). The off-diagonal denotes shocks from (to) others, and diagonal elements capture shocks of its own. In other words, the average contribution of spillovers from shocks to all (other) markets to the total forecast error variance is measured by applying this index. Additionally, this index is flexible and enables identification of the directional spillovers among all markets. Specifically, the directional spillovers received by market i from all other markets l are defined as:

$$Dsp_{i\leftarrow l}\left(H\right)=\frac{\sum_{l=1,\, j\neq i}^{n}\tilde{\varphi}_{il}(H)}{\sum_{i,l=1}^{n}\tilde{\varphi}_{il}(H)}\times 100=\frac{\sum_{l=1,l\neq i}^{n}\tilde{\varphi}_{il}(H)}{n}\times 100. \qquad (5)$$

Similarly, the directional spillovers transmitted by market i to all other markets l are defined as:

$$Dsp_{i\to l}\left(H\right)=\frac{\sum_{l=1,l\neq i}^{n}\tilde{\varphi}_{il}(H)}{\sum_{i,l=1}^{n}\tilde{\varphi}_{il}(H)}\times 100=\frac{\sum_{l=1,l\neq i}^{n}\tilde{\varphi}_{il}(H)}{n}\times 100. \qquad (6)$$

The set of directional spillovers provides a decomposition of total spillovers into those coming from (or to) a particular market. For instance, in the present application this means that this spillover matrix $\varphi(H)$ consists of the main diagonal elements reflecting own-market spillovers, and the off-diagonal elements reflecting cross-market spillovers.

Finally, subtracting Eq. (6) from Eq. (5), we compute the net volatility spillovers from each market to all other markets as:

$$Nsp_i(H)=Dsp_{i\to l}(H)-Dsp_{i\leftarrow l}(H) \qquad (7)$$

The net volatility spillover explains how much the volatility of each market contributes to the volatility in other markets in net terms.

The net pairwise volatility spillovers is computed as:

$$Npsp\left(H\right)=\left(\frac{\tilde{\varphi}_{il}\left(H\right)}{\sum_{l,p=1}^{n}\tilde{\varphi}_{lp}\left(H\right)}-\frac{\tilde{\varphi}_{li}\left(H\right)}{\sum_{i,p=1}^{n}\tilde{\varphi}_{ip}\left(H\right)}\right)\times 100=\left(\frac{\tilde{\varphi}_{il}\left(H\right)-\tilde{\varphi}_{li}\left(H\right)}{n}\right)\times 100 \qquad (8)$$

The net pairwise volatility spillover is simply the difference between gross volatility spillovers transmitted from market i to market l and *vice versa*. We convert all market connectedness into networks. Following the interpretations of Diebold and Yilmaz (2015, 2016), the variance decomposition matrix is treated as the adjacency matrix of a weighted directed network. The elements of this matrix are pairwise directional connectedness. The row sums of this matrix are total directional connectedness i.e., $Dsp_{i\leftarrow l}(H)$ and the column sums are total directional connectedness i.e., $Dsp_{i\to l}(H)$.

Finally, to estimate the dynamic connectedness between markets, Diebold and Yilmez (2009, 2014 and 2015) used the rolling windows approach by using the same measures as discussed above. The rolling window approach not only enables us to capture the time-varying spillovers effects in the system but also allows us to analyze the contribution of each market to the system over time. Moreover, the rolling concept not only helps in managing the issue of time zone, but also helps in managing the outliers resulted from the use of daily squared returns as a proxy of absolute volatility, which generally causes a problem in VAR estimation. In our case, the same also helps in capturing the change in connectedness dynamic during the periods of high volatility. This method has been extensively used in literature to investigate volatility spillovers across markets, for example, Zhang (2017) study volatility connectedness between oil markets and financial markets, Antonakakis et al. (2018) analyzed volatility spillover between oil prices and stock prices of oil and gas firms, Corbet et al. (2018) test the time-varying relationship between cryptocurrencies and financial Assets, Kang et al. (2019) examined the pattern of spillover and connectedness between a broad set of financial assets (equities, commodities, bonds and VIX).

3.2. Data and Preliminary Analysis

In this study, we use daily closing prices data of WilderHill Clean Energy Price Index (CEPI), MSCI World Energy Price Index (WEPI), MSCI World IT Price Index (WIPI), MSCI World Stock Price Index (WSPI), MSCI World Commodity Producers Index (WCPI), VIX index (VIX), US Economic Policy Uncertainty Index (USEPU), US Treasury Benchmark Bond 10 Years (DS) - Red. Yield (USBOND) and West Texas Intermediate (WTI) crude oil price. CEPI is a modified dollar weighted index of 54 companies that are engaged in clean energy business. Companies weighting within the CEPI is based on their role for clean energy, their technological influence and their significance to control pollution. WEPI and WIPI both indices capture large and mid-cap segments across 23 developed market countries. All the securities in energy sector or information technology sector are classified according to the Global Industry Classification Standard. WCPI is a broad global equity index that represents large and mid-cap equity performance of 23 world developed countries. CEPI excludes stocks from emerging markets and covers approximately 85% of market capitalization of each developed country. WCPI is equity-based index that seeks to reflect the performance of producers in three markets, energy, metal and agriculture. All constituent indexes are classified according to Global Industry Classification

Standard. VIX created by Chicago Board Options Exchange is a real time market index, derived from the price inputs of the S&P 500 index options. It measures market risks and investors sentiments. USEPU is based on daily newspapers in United States. These newspapers vary from large national papers to small local newspapers across the country. This index comprises 3 set of terms: economy, uncertainty and legislation and include those articles that cover at least one of these terms. USBOND is a broad, market-value weighted index that measures the performance of US treasury. WTI is a benchmark international crude oil price and primarily representative of US market. The data ranges from December 28, 2000 to December 31, 2018 and are collected from DataStream database. The plots of raw data series displayed in Appendix, Figure A show that CEPI, WEPI, WSPI, WCPI, VIX, USBOND and WTI tends to move together. However, these indices plots show break during 2008 owing to the onset of global financial crisis 2008-09. The plot of WIPI remain consistent most of the time period. The plot of USEPU show big spikes of volatility throughout the sample period which describe that people trust on US economic policy is highly uncertain.

The descriptive statistics of all selected return series are shown in Appendix, Table A. The highest mean returns are observed for WTI followed by WEPI, WEPI and WCPI respectively while lowest mean returns are shown for CEPI. USEPU show highest volatility (in terms of variance coefficient) while WSPI returns indicate lowest volatility. CEPI, WEPI, WSPI, WCPI, USBOND, and WTI returns report negative coefficient of skewness while WIPI, USEPU and VIX shows positive coefficient of skewness. Negative coefficient of skewness imply that negative returns are more frequents than positive returns and *vice versa*. As observed for kurtosis, the dataset of USEPU reports platykurtic distribution while the dataset of all the remaining returns series exhibit leptokurtic distribution. The returns series that report leptokurtic distribution imply higher probability of realizing positive returns than those returns series that exhibit platykurtic distribution. Test statistics of Jarque and Bera normality test clearly rejects the null hypothesis of the normal distribution, indicating that data does not follow the normal distribution. ERS unit root test results clearly show that all return series are stationary at level. Finally, Ljung–Box test statistics for standard residuals and squared standardized residuals as well as Lagrange Multiplier test at lag 20 allow rejection of the null hypothesis of no serial correlation in all series. The results of correlation matrix presented in Appendix, Table B show that the highest correlation is observed between WCPI and WEPI returns, equivalent to 0.97, followed by the correlation between WCPI and WSPI which is 0.84 and between WIPI and WSPI which is 0.82. The lowest correlation is perceived between USEPU and WSPI which is -0.003.

4. Empirical Findings and Discussions

4.1 DY-Spillovers Results

Table 1 display the results of DY (2012) connectedness measures using the full sample. The empirical results show that total connectedness in the system is 57.76% indicating that energy and financial markets are highly interdepended. The share of volatility shocks that are transferred from one market to other varies within the system. The highest spillovers are reported from WEPI to WCPI - the share of volatility transmitted from WEPI to WCPI is 23.48%. Similarly, the share of volatility shocks that are transferred from USEPU to WCPI and WSPI is almost zero. Regarding the contribution to others, the total contribution of WSPI to other markets is highest in the system and USEPU is lowest in the system. Further, the realized variation in the returns of WEPI and WCPI futures that are transmitted to other markets in our system is more than 90%. The results of directional volatility spillovers from all markets to one specific market varies from 0.63% to 76.86% for USEPU and WSPI respectively. This implies that WSPI is the most affected by the shocks from other markets while USEPU is the least affected by the shocks from other markets. The result of net spillovers returns for each individual market show that WTI is a net receiver of volatility implies that oil market receives more volatility from other markets then it contributes to. In other words, volatility in oil market is affected by financial system. This result is contradictory to Arouri et al. (2011); Awartani and Maghyereh (2013) that oil market volatility is the net transmitter of volatility shocks to stock markets. In financial market, CEPI, WEPI, WSPI and WCPI are the net transmitters of volatility (1.72%, 15.85%, 22.86% and 15.9% respectively) to other markets. On the other hand, WIPI, USBOND are the net receivers of volatility (-2.18%, -20.82% respectively).

Table 1: DY-VAR Static Spillover

	CEPI	WEPI	WIPI	WSPI	USBOND	WCPI	USEPU	VIX	WTI	FROM
CEPI	28.92	11.78	15.421	16.585	2.899	11.974	0.006	10.417	1.999	71.08
WEPI	10.392	25.096	7.449	16.187	2.66	23.831	0.002	7.548	6.836	74.904
WIPI	15.956	8.783	29.961	20.354	3.059	9.306	0.002	11.776	0.802	70.039
WSPI	13.635	14.896	15.957	23.14	3.175	16.076	0	11.115	2.006	76.86
USBOND	5.939	6.3	6.073	8.224	59.224	6.123	0.029	5.433	2.656	40.776
WCPI	10.658	23.479	7.909	17.244	2.513	24.615	0.001	7.461	6.12	75.385
USEPU	0.02	0.079	0.134	0.158	0.012	0.102	99.371	0.115	0.008	0.629
VIX	12.246	10.188	13.321	16.038	3.137	9.999	0.01	33.856	1.206	66.144
WTI	3.956	15.245	1.593	4.935	2.499	13.872	0.051	1.909	55.94	44.06
Contribution TO others	72.802	90.75	67.858	99.724	19.954	91.285	0.1	55.772	21.633	519.878
Contribution including own	101.722	115.846	97.819	122.863	79.178	115.9	99.471	89.628	77.573	TCI = 57.764
Net spillovers	1.722	15.846	-2.181	22.863	-20.822	15.9	-0.529	-10.372	-22.427	

Note: (1) CEPI (WilderHill Clean Energy Price Index); (WEPI) MSCI World Energy Price Index), WIPI (MSCI World IT Price Index); WSPI (MSCI World Stock Price Index); WCPI (MSCI World Commodity Producers Index) VIX (VIX index); USEPU (US Economic Policy Uncertainty Index); USBOND (US Treasury Benchmark Bond 10 Years (DS) - Red. Yield) and WTI (West Texas Intermediate). (2) DY-VAR Static Spillover (Diebold and Yilmez-Vector Autoregressive Static Spillover).

Using the DY spillovers table, it is also possible to construct a 'net pairwise spillovers' matrix for all pairs. The results reported in Table 2 suggest that WEPI acts as a net contributor of volatility with respect to CEPI while WIPI acts as a net pairwise receivers of volatility against CEPI, and WEPI. The WSPI, on the other hand, acts as a net contributor of volatility with respect to CEPI, WEPI and WIPI. WCPI acts as a net contributor of volatility with respect to CEPI, WEPI, WIPI and US Bond while net receiver of volatility with respect to WSPI. Furthermore, USBOND, USEPU, VIX and WTI acts as a net receiver of volatility in system. It is, thus, suggestive that WTI, USBOND, USEPU and WIPI are the net pairwise receivers of volatility in our system while WEPI and WSPI are net pairwise contributor of volatility. Our result support the study of Malik and Ewing (2009); Arouri et al. (2011) and (2012). Malik and Ewing (2009) examined the relationship between sector index volatilities and crude oil price volatility using the data on six US sectoral stock market indices, namely Financials, Industrials, Consumer Services, Health Care and Technology. Their findings suggest heterogeneous responses from the different sectoral indices. Arouri et al. (2011) focused the several US and European industrial sectors (i.e. Automobile & Parts, Financials, Industrials, Basic Materials, Technology, Telecommunications and Utilities) for the period 1989-2009. The estimated results are different not only among the different sectors (as already documented by Malik and Ewing, 2009), but also between the two financial markets. In a subsequent study, Arouri et al. (2012) corroborate the findings of Arouri et al. (2011). Turning to studies that utilize aggregate stock market indices, Vo (2011) investigates the inter-dependence between S&P500 index and WTI crude oil price volatilities for the period 1999-2008. The result shows a mutual inter-dependence between the two market volatilities. Similar results are also reported by Mensi et al. (2013). Ewing and Malik (2016) also support the findings of Vo (2011) and Mensi et al. (2013), focusing on WTI and S&P500 volatilities, for the period 1996-2013. It is evident from the study's results that there are significant cross-market volatility effects. Nevertheless, they also report that the oil price volatility receives stronger effects from the stock market volatility, as compared with the reverse. Thus, our study results are in line with disaggregated studies that explain heterogeneous responses from the different sectoral indices and also support the finding of Antonakakis et al., (2018) that disaggregated approach has advantage over aggregated approach.

Table 2: Net DY-VAR Static Spillovers

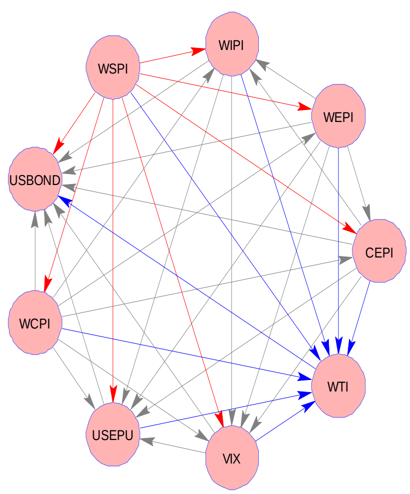
	CEPI	**WEPI**	**WIPI**	**WSPI**	**USBOND**	**WCPI**	**USEPU**	**VIX**	**WTI**
CEPI	0	0.154222	-0.059444	0.327778	-0.33778	0.146222	-0.00156	-0.20322	-0.21744
WEPI		0	-0.148222	0.143444	-0.40444	0.039111	-0.00856	-0.29333	-0.93433
WIPI			0	0.488556	-0.33489	0.155222	-0.01467	-0.17167	-0.08789
WSPI				0	-0.561	-0.12978	-0.01756	-0.547	-0.32544
USBOND					0	0.401111	0.001889	0.255111	0.017444
WCPI						0	-0.01122	-0.282	-0.86133
USEPU							0	0.011667	-0.00478
VIX								0	-0.07811
WTI									0

Note: (1) CEPI (WilderHill Clean Energy Price Index); (WEPI) MSCI World Energy Price Index), WIPI (MSCI World IT Price Index); WSPI (MSCI World Stock Price Index); WCPI (MSCI World Commodity Producers Index) VIX (VIX index); USEPU (US Economic Policy Uncertainty Index); USBOND (US Treasury Benchmark Bond 10 Years (DS) - Red. Yield) and WTI (West Texas Intermediate). (2) DY-VAR Static Spillover (Diebold and Yilmez-Vector Autoregressive Static Spillover).

In Figure 1, we have plotted the net pairwise directional connectedness of the oil and financial market in time domain. The direction of arrows explains net directional connectedness between series. It is clear from the graph that WSPI stock returns play a leading role in total connectedness followed by WCPI stock returns. The net pairwise directional connectedness from

WSPI to CEPI, WIPI, WEPI, WCPI, USBOND, USEPU, VIX and WTI are the top eight among all net pairwise directional spillovers contributors followed by WEPI which is the top six amongst all net pairwise directional spillovers contributors including oil market. CEPI stock returns explain more than they receive from all other financial markets. The net pairwise directional connectedness to WSPI, CEPI, WIPI, WEPI, WCPI, WTI, USEPU and VIX from USBOND is the top eight amongst all net pairwise directional spillovers receivers followed by WTI which is the top seven amongst all net pairwise directional spillovers receivers. The results confirm our previous findings that WSPI and WEPI play a dominant role in financial markets while USBOND, USEPU and VIX role is limited in financial market. Further, our results explain that the role of oil/energy price volatility is limited, rather they receive information from financial markets. These findings are contradictory to previous findings (e.g. Kilian and Park, 2009; Abhyankar et al. 2013 and Kang et al. 2016) that claim that oil shocks play an important role in affecting stock markets returns. Moreover, oil shocks are not exogenous, they are the part of financial markets and affected by the shocks in global financial system. However, our results support the study of Zhang (2017) that concluded that the role of oil shocks is limited in global financial system.

Figure 1: Pairwise Plots of Directional Connectedness

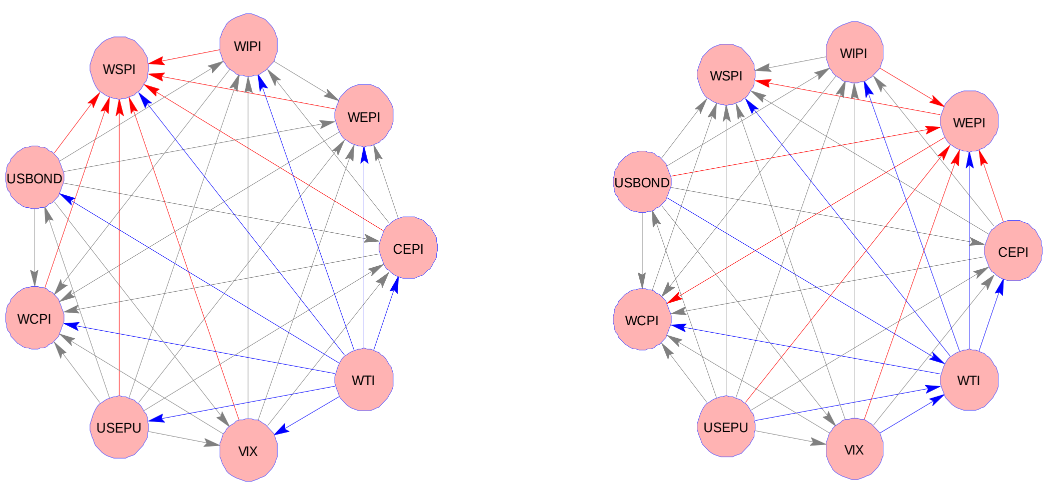


Note: The direction of arrows represents net pairwise directional connectedness between series. The color of lines explains the strength of pairwise directional connectedness from red (strongest) to blue and gray (weakest).

To further clarify our results, we break the data into three periods: pre-crisis, crisis and post crisis[1]. However, the results are surprising (see Figure 2). Before the pre-crisis period, oil price shocks are net pairwise contributors to all financial markets. WSPI is the net pairwise receiver of volatility from all financial markets including crude oil followed by WEPI which is receiving volatility from six markets. The shocks to economic policy index are transmitting volatility to all financial markets except oil market. Network plots of crisis and post-crisis spillover show that the role of US economic policy is dominant in global financial markets and is the major source of transmitting shocks. Shocks to oil returns explain more than they receive from all other financial markets, implies that oil market is playing their significant role in financial market during crisis and post crisis period. Thus, in our results we can clearly observe the role of financial crisis in changing market structure and are in line with the findings of Creti et al., (2013); Gkanoutak-Leventis and Nesvetailova, (2015).

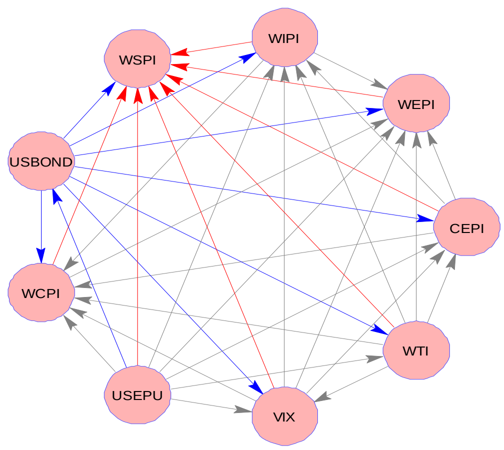
Figure 2: Pairwise Plots of Directional Connectedness

(a) Pre-Crisis Spillovers Network (b) Crisis Spillovers Network



[1] 2008 global financial crisis

(c) Post Crisis Spillovers Network



Note: The direction of arrows represents net pairwise directional connectedness between series. The color of lines explain the strength of pairwise directional connectedness from red (strongest) to blue and gray (weakest).

4.2 Hedging and portfolio weights Analysis

This section examined the implications of above-mentioned results for international portfolio diversification and risk management. As noted above, the results of pairwise net directional connectedness have changed when sample is divided into three period: pre-financial crisis, financial crisis and post financial crisis. These results arise the question of whether optimal diversification strategies changed during the aforementioned 3 sub-periods. To answer this question, conditional variance estimates can be used to construct the hedge ratios and optimal portfolio weight of assets during the aforementioned 3 sub-periods. In particular, the conditional variance estimates have been used to construct the optimal hedge ratios and portfolio weights following (see *inter alia*, Kroner and Sultan, 1993; Kroner and Ng., 1998; Hammoudeh et al., 2010; Chang et al., 2011; Maghyereh et al., 2017; Antonakakis et al., 2018). Similarly, Kang et al., (2019) used the same approach to construct the optimal hedge ratio and portfolio weights however using the volatility spillover indices[2].

For the construction the optimal hedge ratios, we assume that investors are taking a long position in the oil and stock price volatility when future volatility in either of the asset is expected

2 We should pointed out that our analysis is mainly addressing the ex-post optimal hedge ratios and portfolio weights rather than out-of-sample analysis (Antonakakis et al. 2018 & Kang et al., 2019).

to be higher compared to the current volatility level. A short position is expected to be taken when future volatility is expected to decrease. Investors might be willing to hedge their long/short positions as a precautionary measure for adverse movement of volatility. Specifically, the hedge ratio between long position in WTI volatility (denoted as volatility o) and short position in one of stock market volatility (denoted as volatility s) is represented as

$$B_t^{os} = \frac{h_t^{os}}{h_t^{s}} .$$

An investor always tries to minimize the risk of their portfolio for a given expected return. Given that objective, the optimal weight of an asset w_t^{os} in a one dollar portfolio consisting of WTI volatility o and stock market volatility s is defined as

$$w_t^{os} = \frac{h_t^{s} - h_t^{os}}{h_t^{o} - 2_t^{os} + h_t^{s}} .$$

Where h_t^{s} is the conditional volatility of stock market at time t, h_t^{o} is the conditional volatility of oil market at time t and h_t^{os} is the conditional covariance between oil and stock market.at time t.

The following restriction can be imposed on the optimal portfolio weights if there is no possibility of short-selling:

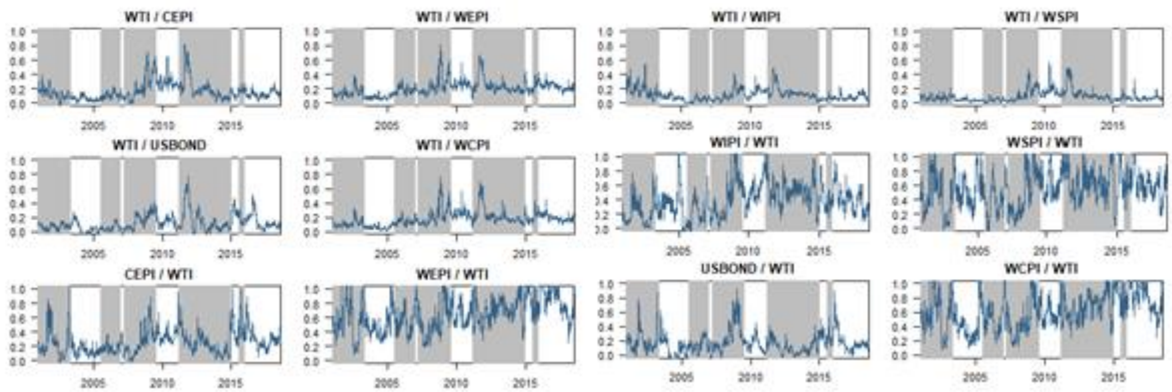
$$w_t^{os} = \begin{cases} 0, & if\ w_t^{os} < 0 \\ w_t^{os}, & if\ 0 \le w_t^{os} \le 1 \\ 1, & if\ w_t^{os} > 1 \end{cases} .$$

Where w_t^{os} is the weight of WTI volatility in a one dollar portfolio of oil volatility o and one of the stock price volatility s at time t. Thus, $1 - w_t^{os}$ is the weight of one of the stock price volatility s at time t in the aforementioned portfolio.

The dynamic hedge ratios and portfolio weights are plotted in Figure 3 and 4. In Figure 3, we see that pairwise hedge ratio shows considerable volatility during the turbulent period of 2008-

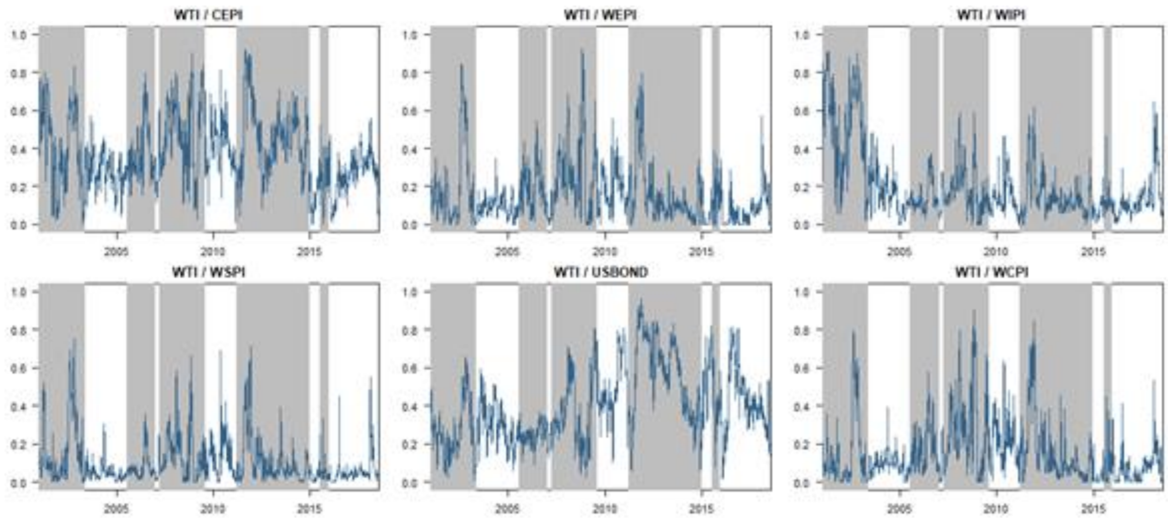
09, implies that increase in hedging cost due to increase in number of contracts during that period required hedging strategy. Nevertheless, this does not hold for all hedge ratios. The maximum hedge ratio between WTI/USBOND is recorded in post financial crisis period. Moreover, long position in WTI volatility significantly reduce the hedge ratios as compared to those when short position is taken in WTI volatility. This finding supports the results presented in previous section that oil price is mainly impacted by the financial market volatility in long term. The graphical representation of dynamic portfolio weights displayed in Figure 4 show extreme volatility suggesting that active portfolio management is required to invest in these volatilities.

Figure 3. Dynamic hedge ratios (long/short)



Note: Shading areas denote US recessions as defined by the National Bureau of Economic Research (NBER) business cycles dating committee.

Figure 4. Dynamic Portfolio Weights



Note: Shading areas denote US recessions as defined by the National Bureau of Economic Research (NBER) business cycles dating committee.

As noted in Table 3, the average value of hedge ratio between a long position in financial market stock indices and short position in WTI volatility varies from 16 cents (USBOND/WTI) to 64 cents (WEPI/WTI). It means a $1 long position in USBOND can be hedged for 16 cents with a short position in WTI. Similarly, a $1 long position in WEPI can be hedged for 64 cents with a short position in WTI. Thus, WEPI is the least useful stock index to hedge against WTI volatility. Furthermore, the results of long position in WTI and short position in financial market stock indices show that the cheapest average hedge is between WTI/WSPI and the most expensive hedge is between WTI/WEPI. We note that average hedge ratios for a $1 long position in financial market stock indices do not show considerable change in the pre-during and post financial crisis periods, although hedging was cheapest in the pre and during financial crisis period. Likewise, we do not observe noticeable change in the average hedge ratios for a $1 long position in WTI in 3 sub- crisis periods.

Table 3: Hedge ratios (long/short) Summary Statistics

	Full Sample				PRE FINANCIAL CRISIS				FINANCIAL CRISIS				POST FINANCIAL CRISIS			
Panel A: Hedge ratios (long/short)																
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
CEPI WTI	2.52E-01	0.166481	-0.02518	1.101957	0.191896	0.164117	-0.02518	1.101957	0.168432	0.060221	7.15E-02	3.60E-01	2.27E-01	0.117161	3.77E-02	3.95E-01
WEPI WTI	6.44E-01	0.248758	0.077395	1.64539	0.525515	0.252157	0.077395	1.596334	0.50808	0.15169	2.26E-01	8.67E-01	7.84E-01	0.193195	4.80E-01	1.15E+00

WIPI WTI	3.83E-01	0.232885	-0.18063	1.738435	0.257594	0.207994	-0.18063	1.174832	0.209833	0.151276	-1.59E-01	5.88E-01	3.72E-01	0.223246	3.59E-02	7.31E-01
WSPI WTI	5.57E-01	0.291576	-0.08003	2.104103	0.488327	0.27995	-0.02435	1.704926	0.349419	0.21751	-8.00E-02	9.13E-01	5.13E-01	0.273183	6.48E-02	8.87E-01
USBOND WTI	1.62E-01	0.146955	-0.15795	0.921054	0.142725	0.153427	-0.15795	0.874245	0.142251	0.085166	-1.95E-02	3.51E-01	6.73E-02	0.089301	-6.83E-02	2.25E-01
WCPI WTI	6.11E-01	0.269959	0.067707	1.731595	0.502418	0.286128	0.067707	1.663078	0.458974	0.149111	1.58E-01	7.67E-01	7.50E-01	0.256353	3.41E-01	1.22E+00
WTI CEPI	1.60E-01	0.127858	-0.04267	0.80881	0.093034	0.069791	-0.04267	0.379568	0.106822	0.042682	3.19E-02	2.30E-01	9.44E-02	0.036203	4.80E-02	2.03E-01
WEPI CEPI	5.97E-01	0.216162	0.114165	1.322724	0.481021	0.168127	0.114165	1.317279	0.489059	0.188389	2.13E-01	9.37E-01	5.49E-01	0.247634	3.12E-01	1.01E+00
WIPI CEPI	8.49E-01	0.282913	0.206817	1.844765	0.542445	0.170536	0.206817	1.1653	0.857468	0.144178	4.89E-01	1.26E+00	1.02E+00	0.168369	8.00E-01	1.35E+00
WSPI CEPI	1.14E+00	0.263151	0.441059	2.427506	1.06798	0.327532	0.50364	2.427506	1.199808	0.151323	8.35E-01	1.68E+00	1.30E+00	0.093781	1.09E+00	1.49E+00
USBOND CEPI	2.14E-01	0.142968	-0.06724	1.097695	0.210385	0.129039	-0.01293	0.685329	0.147148	0.068616	-6.72E-02	2.82E-01	3.56E-01	0.13872	1.40E-01	6.99E-01
WCPI CEPI	6.29E-01	0.201061	0.194509	1.365429	0.565376	0.170403	0.194509	1.365429	0.547457	0.183606	2.10E-01	1.02E+00	5.57E-01	0.217216	3.14E-01	9.53E-01
WTI WEPI	2.05E-01	0.106875	0.031502	0.80839	0.113584	0.059809	0.031502	0.392585	0.180216	0.050071	8.33E-02	3.38E-01	1.96E-01	0.032172	1.42E-01	2.73E-01
CEPI WEPI	3.00E-01	0.11807	0.054183	0.762319	0.205581	0.079804	0.054183	0.602389	0.269506	0.061851	9.78E-02	4.63E-01	2.63E-01	0.03551	2.21E-01	3.55E-01
WIPI WEPI	4.53E-01	0.216455	0.043342	1.129014	0.191799	0.087719	0.043342	0.505414	0.371198	0.096897	1.58E-01	7.57E-01	3.18E-01	0.061197	2.24E-01	4.19E-01
WSPI WEPI	8.47E-01	0.2036	0.182492	1.536925	0.64004	0.176009	0.182492	1.212217	0.870854	0.181018	5.21E-01	1.40E+00	7.51E-01	0.125536	5.61E-01	9.41E-01
USBOND WEPI	1.35E-01	0.117721	-0.10142	1.001085	0.107579	0.088513	-0.0217	0.50192	0.023187	0.047789	-1.01E-01	1.40E-01	1.13E-01	0.045325	4.12E-02	2.36E-01
WCPI WEPI	9.89E-01	0.094243	0.711717	1.437482	1.051245	0.085988	0.834273	1.437482	1.01298	0.098505	8.23E-01	1.27E+00	9.56E-01	0.093837	7.64E-01	1.09E+00
WTI WIPI	1.12E-01	0.080771	-0.01827	0.5373	0.12971	0.09178	-0.0101	0.5373	0.044868	0.035097	-1.58E-02	1.53E-01	5.25E-02	0.024604	5.92E-03	1.07E-01
CEPI WIPI	3.97E-01	0.187234	0.106134	1.260375	0.572931	0.262992	0.161239	1.260375	0.268009	0.073529	1.06E-01	4.80E-01	3.39E-01	0.015567	3.09E-01	3.73E-01
WEPI WIPI	4.03E-01	0.209847	0.062059	1.974164	0.497226	0.332976	0.086654	1.974164	0.203284	0.072943	6.21E-02	3.76E-01	2.26E-01	0.11436	1.08E-01	4.28E-01
WSPI WIPI	1.08E+00	0.422389	0.500339	3.321521	1.547515	0.567883	0.544735	3.321521	0.934734	0.152164	5.33E-01	1.28E+00	9.19E-01	0.075275	7.69E-01	1.06E+00
USBOND WIPI	1.75E-01	0.134926	0.016935	0.951989	0.266723	0.193188	0.024885	0.951989	0.118753	0.03632	2.96E-02	2.05E-01	2.36E-01	0.076074	1.22E-01	4.41E-01
WCPI WIPI	4.23E-01	0.220005	0.084086	1.91144	0.563008	0.340209	0.099489	1.91144	0.244501	0.084408	8.41E-02	4.28E-01	2.51E-01	0.094044	1.33E-01	4.17E-01
WTI WSPI	9.01E-02	0.077763	-0.01376	0.569001	0.056074	0.031689	-0.01376	0.215698	0.039385	0.025612	-6.02E-03	1.00E-01	3.97E-02	0.018277	1.90E-02	8.94E-02
CEPI WSPI	2.80E-01	0.105623	0.056367	0.8025	0.273303	0.126457	0.056367	0.707559	0.205178	0.045704	1.17E-01	3.47E-01	2.53E-01	0.046434	1.88E-01	3.35E-01
WEPI WSPI	4.16E-01	0.149373	0.090622	0.928616	0.375476	0.134281	0.093212	0.85827	0.259487	0.080062	1.47E-01	4.96E-01	3.03E-01	0.146214	1.61E-01	5.82E-01
WIPI WSPI	5.55E-01	0.172596	0.150553	1.213245	0.371339	0.109462	0.150553	0.672286	0.512187	0.061132	3.72E-01	7.42E-01	5.34E-01	0.110329	3.82E-01	7.03E-01
USBOND WSPI	1.39E-01	0.103954	0.014543	0.811016	0.139051	0.112174	0.014543	0.637196	0.098198	0.022933	5.11E-02	1.79E-01	1.78E-01	0.061235	1.21E-01	3.70E-01
WCPI WSPI	4.74E-01	0.143683	0.134953	1.05338	0.474483	0.149503	0.174838	1.05338	0.337474	0.090705	1.87E-01	6.13E-01	3.67E-01	0.133492	1.93E-01	5.98E-01

WTI USBOND	1.19E-01	0.11992	-0.09212	0.780428	0.05798	0.060714	-0.09212	0.274509	0.058059	0.045655	-5.42E-03	1.85E-01	2.12E-02	0.026885	-1.94E-02	8.39E-02
CEPI USBOND	2.36E-01	0.153162	-0.06161	0.870476	0.162908	0.102634	-0.00241	0.518673	0.098366	0.052143	-1.08E-02	2.02E-01	2.08E-01	0.038742	1.34E-01	2.90E-01
WEPI USBOND	3.07E-01	0.236706	-0.05968	1.122366	0.168596	0.111591	-0.03659	0.599741	0.034297	0.052148	-5.97E-02	1.72E-01	1.39E-01	0.063348	5.77E-02	2.45E-01
WIPI USBOND	4.12E-01	0.256727	0.015436	1.438476	0.199837	0.117814	0.015436	0.5351	0.252236	0.122218	2.87E-02	5.03E-01	4.16E-01	0.05332	3.08E-01	5.46E-01
WSPI USBOND	6.03E-01	0.340341	0.06413	2.06176	0.36999	0.158018	0.066967	0.835123	0.367844	0.14887	6.41E-02	7.12E-01	5.61E-01	0.123272	3.36E-01	7.28E-01
WCPI USBOND	3.30E-01	0.242515	-0.08023	1.27811	0.20657	0.129705	-0.08023	0.673956	0.051831	0.057703	-4.02E-02	2.39E-01	1.65E-01	0.048874	8.93E-02	2.48E-01
WTI WCPI	1.78E-01	0.108255	0.007769	0.768408	0.085873	0.049997	0.007769	0.332224	0.135564	0.043656	4.89E-02	2.94E-01	1.71E-01	0.031319	1.14E-01	2.52E-01
CEPI WCPI	2.90E-01	0.120065	0.046585	0.754407	0.194441	0.07341	0.050411	0.576389	0.256285	0.062474	8.83E-02	4.66E-01	2.58E-01	0.036053	2.11E-01	3.35E-01
WEPI WCPI	8.84E-01	0.085066	0.624693	1.240775	0.833593	0.059272	0.624693	0.98767	0.844392	0.072656	6.90E-01	1.04E+00	9.04E-01	0.098318	7.63E-01	1.13E+00
WIPI WCPI	4.32E-01	0.215903	0.03844	1.169648	0.179783	0.085467	0.03844	0.468942	0.374855	0.102316	1.49E-01	7.56E-01	3.52E-01	0.085609	2.47E-01	4.88E-01
WSPI WCPI	8.82E-01	0.215073	0.195213	1.458126	0.653055	0.186038	0.195213	1.118598	0.948894	0.16719	6.15E-01	1.40E+00	8.88E-01	0.121215	6.65E-01	1.13E+00
USBOND WCPI	1.33E-01	0.112769	-0.0612	0.970661	0.101775	0.080421	-0.02098	0.512906	0.032587	0.037357	-6.12E-02	1.04E-01	1.34E-01	0.053356	6.38E-02	3.01E-01

The results of portfolio weights are shown in Table 4. For the full sample period, the highest average optimal weight is observed for WSPI/USBOND portfolio which is 0.85, indicating that for a $1 portfolio, 85 cents will be investment in WSPI and the remaining 15 cents will be investment in USBOND. The average optimal weight for the WTI/CEPI portfolio explains that 37 cents will be invested in oil market and the remaining 63 cents will be invested in CEPI index. The lowest average optimal weight is observed for WTI/WSPI portfolio which is 0.10 suggesting that 0.1 cent will be invested in WTI and the remaining 99 cents will be invested in WSPI index. Finally, WTI volatilities shows lowest average weight for most of the portfolios in the post financial crisis period.

In general, the evidence supports that hedge ratios are volatile over time reaching a peak during the 2008-09 financial crisis except the WTI/USBOND hedge ratios that reach their peak in the post-financial crisis period. The average hedge ratios in the WTI volatility do not change notably in the pre-, during and post-financial crisis periods. The results show that the optimal weights and hedge ratio for the oil asset in the hedged portfolios varies from one financial market to another, provide evidence in support of disaggregated analysis compared to aggregated analysis. This result is in line with Antonakakis et al., (2018) that disaggregated approach has advantage over aggregate analysis because aggregated approach is not particularly useful for international portfolio diversification and risk management analysis as portfolio managers and investors primarily interest is on disaggregated investment choice. Similar results are observed by DY-VAR analysis. Likewise, our hedge ratios between oil and sector stock markets permit us to effectively hedge the oil price risk using the short position of sector stock indices. The results show that hedging strategies involving oil and stock assets make it possible to reduce portfolio risk (variance) considerably. Overall, the result support the findings of Sardovsky (2012) that oil is a good hedge against clean energy and technology companies; Arouri et al., (2011) that oil can be considered a dynamic and valuable asset that helps improve the risk-adjusted performance of a well-diversified portfolio of sector stocks and serves to hedge oil risk more effectively. For robustness check, we have estimated a large portfolio including all seven returns for WTI hedging analysis. The results are presented in Appendix, Table-C.

Table 4: Portfolio Weights Summary Statistics

	Full Sample				PRE FINANCIAL CRISIS				FINANCIAL CRISIS				POST FINANCIAL CRISIS			
	Panel B: Portfolio weights															
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
WTI CEPI	0.374048	0.183725	0	0.919376	0.341838	0.18119	0	0.834109	0.373167	0.139939	0.146874	0.793369	0.31307	0.160685	0.118097	0.607533
WTI WEPI	0.154291	0.154769	0	0.921635	0.142414	0.160999	0	0.841409	0.196626	0.111599	0.013751	0.545851	0.073008	0.064515	0	0.181947
WTI WIPI	0.199209	0.181749	0	0.91483	0.350881	0.255722	0	0.914829	0.146712	0.077571	0.028953	0.375998	0.117832	0.084928	0.027438	0.276993
WTI WSPI	0.100886	0.12082	0	0.752833	0.108838	0.146691	0	0.752833	0.078441	0.065513	0.00844	0.356198	0.076482	0.086325	0.004955	0.245558
WTI USBOND	0.399907	0.19841	0.008032	0.961648	0.278769	0.129978	0.008032	0.65529	0.249919	0.054502	0.088736	0.366433	0.228998	0.068854	0.12871	0.343895
WTI WCPI	0.152487	0.156977	0	0.904484	0.121488	0.145119	0	0.794883	0.176053	0.107785	0.03396	0.575151	0.0877	0.096256	0	0.286024
CEPI WEPI	0.239822	0.162701	0	0.831761	0.240291	0.145464	0	0.831761	0.295733	0.149016	0.030654	0.669159	0.261342	0.165612	0	0.522658
CEPI WIPI	0.193798	0.273227	0	1	0.527425	0.314373	0	1	0.069524	0.062097	0	0.49098	0.031243	0.037176	0	0.114565
CEPI WSPI	0.030908	0.082106	0	0.83738	0.056806	0.112033	0	0.699042	0.001955	0.009448	0	0.077417	0	0	0	0
CEPI USBOND	0.517298	0.209578	0	0.981858	0.421093	0.157152	0.077114	0.84035	0.360836	0.094959	0.118662	0.550128	0.342319	0.122758	0.096232	0.488394
CEPI WCPI	0.212476	0.154251	0	0.802005	0.181165	0.122753	0	0.802005	0.236296	0.125231	0	0.601822	0.232384	0.141498	0.017359	0.52473
WEPI WIPI	0.435019	0.242083	0	1	0.727422	0.208671	0.247159	1	0.3077	0.129327	0.063523	0.7088	0.375696	0.113223	0.186157	0.565479
WEPI WSPI	0.147988	0.168419	0	0.945258	0.278096	0.203956	0	0.945258	0.076264	0.083228	0	0.382746	0.17399	0.170226	0.013782	0.512794
WEPI USBOND	0.699446	0.188583	0	1	0.645544	0.153417	0.062527	0.90455	0.50392	0.107774	0.269018	0.727053	0.550662	0.068397	0.409158	0.650371
WEPI WCPI	0.281674	0.356259	0	1	0.070153	0.163769	0	0.922134	0.192467	0.275559	0	1	0.345963	0.396781	0	1
WIPI WSPI	0.16499	0.244762	0	1	0.018547	0.064373	0	0.625765	0.116542	0.151167	0	0.715898	0.129435	0.131177	0	0.413533
WIPI USBOND	0.714657	0.250309	0.010817	1	0.4352	0.262416	0.010817	0.865639	0.686049	0.100822	0.431786	0.843394	0.697159	0.089042	0.457021	0.789195
WIPI WCPI	0.530737	0.254497	0	1	0.226186	0.198977	0	0.747146	0.644837	0.142512	0.223556	0.902456	0.620379	0.083838	0.520888	0.821294

WSPI USBOND	0.855446	0.162616	0.079558	1	0.772011	0.184179	0.097778	0.968691	0.815666	0.109977	0.414593	0.950596	0.828252	0.128315	0.557899	0.940831
WSPI WCPI	0.837919	0.200438	0	1	0.651479	0.244599	0	1	0.929627	0.101194	0.56714	1	0.886567	0.112899	0.689186	1
USBOND WCPI	0.274441	0.184754	0	0.994879	0.297254	0.146049	0.066109	0.933991	0.45083	0.116787	0.218305	0.746892	0.436459	0.090303	0.271341	0.596087

5. Conclusion and policy implications

In this study, we explore the time patterns of volatility spillovers between conventional and non-conventional energy prices and stock prices of global financial markets, namely; WilderHill Clean Energy Price Index, MSCI World Energy Price Index, MSCI World IT Price Index, MSCI World Stock Price Index, MSCI World Commodity Price Index, US Treasury Benchmark Bond 10 Years. In addition, WTI crude oil price, VIX index and US Economic Policy Uncertainty Index are included in order to control for the degree of macroeconomic uncertainty and financial risk globally over the period December 28, 2000 to December 31, 2018. For this purpose, we employ a Diebold and Yilmaz (DY, 2009, 2012 and 2014) time domain connectedness measures to examine volatility spillover across future markets. Dynamic connectedness is also examined with rolling window methods in time domain. Finally, hedge ratios and portfolio weights are calculated for building optimal weights to minimize the risk.

The market for clean energy has experienced remarkable growth during the last decade. Global installation capacity of clean energy reached a new high record of 139.7 GW in 2017 (New Energy Finance, 2018) and expectation for further development in near future. This development is not the result of single factor but rather a combination of numerous economic and societal concerns associated with the depletion of natural resources, consistent rise in environmental pollution and the use of energy consumption in economic growth. Apart from these, the financial performance of clean energy companies also has a crucial impact on the future development of the clean energy sector because companies' profitability is positively related to their success in acquiring private capital for infrastructure investment. Therefore, a better knowledge of all these driving forces is of high interest not only to investors but also policy makers in order to forecast risk for hedging and portfolio diversification and evaluate and adjust the clean energy policy landscape to facilitate the transition towards a sustainable energy system.

The main findings of the study can be summarized in three steps. First, the results from DY (2012) method reveals high interdependence between oil and financial markets volatilities. The results from pairwise net directional connectedness show that world stock returns play a leading role in total connectedness followed by commodity stock returns. WTI is highly affected by the shocks from financial markets. This result is in line with the findings of Zhang (2017) that concluded that the role of oil shocks is limited in global financial system.

Second, the impact of energy market become strong in global financial market when data is divided into pre, during and post financial crisis period. On the basis of these findings, it can be concluded that volatility in energy market occasionally contribute to the global financial system significantly and its role become trivial in long-term. Furthermore, the role of US economic policy become active in 3 aforementioned periods.

Third, we study the existence of optimal diversification strategies into 3 sub-crisis period. The evidence reveals that hedge ratios are volatile over time and reaching the peak during the turbulent period of 2008-09 The average hedge ratio in WTI volatility do not show noticeable change in the 3 aforementioned periods. The optimal portfolio between oil prices and stock prices are heavily weighted to the stock market.

These empirical evidences suggest that fluctuation in oil prices is not the key factor that impacts the stock price movement. Global stock markets have enough power to change their movement according to the business environment that would be less dependent on the oil market. Finally, the results of this study are important for investors, financial managers, and portfolio managers in handling market uncertainty in relation with the advent of oil price shocks. The findings are also relevant in identifying hedging strategies that minimize the diversification of risk. The onset of global financial crisis significantly changes the world economic and financial structure. Different sectors of the economy become more connectedness and tends to move in a more systemic way. Therefore, it is essential for investors to assess the timings and the type of global shocks when dealing with portfolios consisting of oil and stocks.

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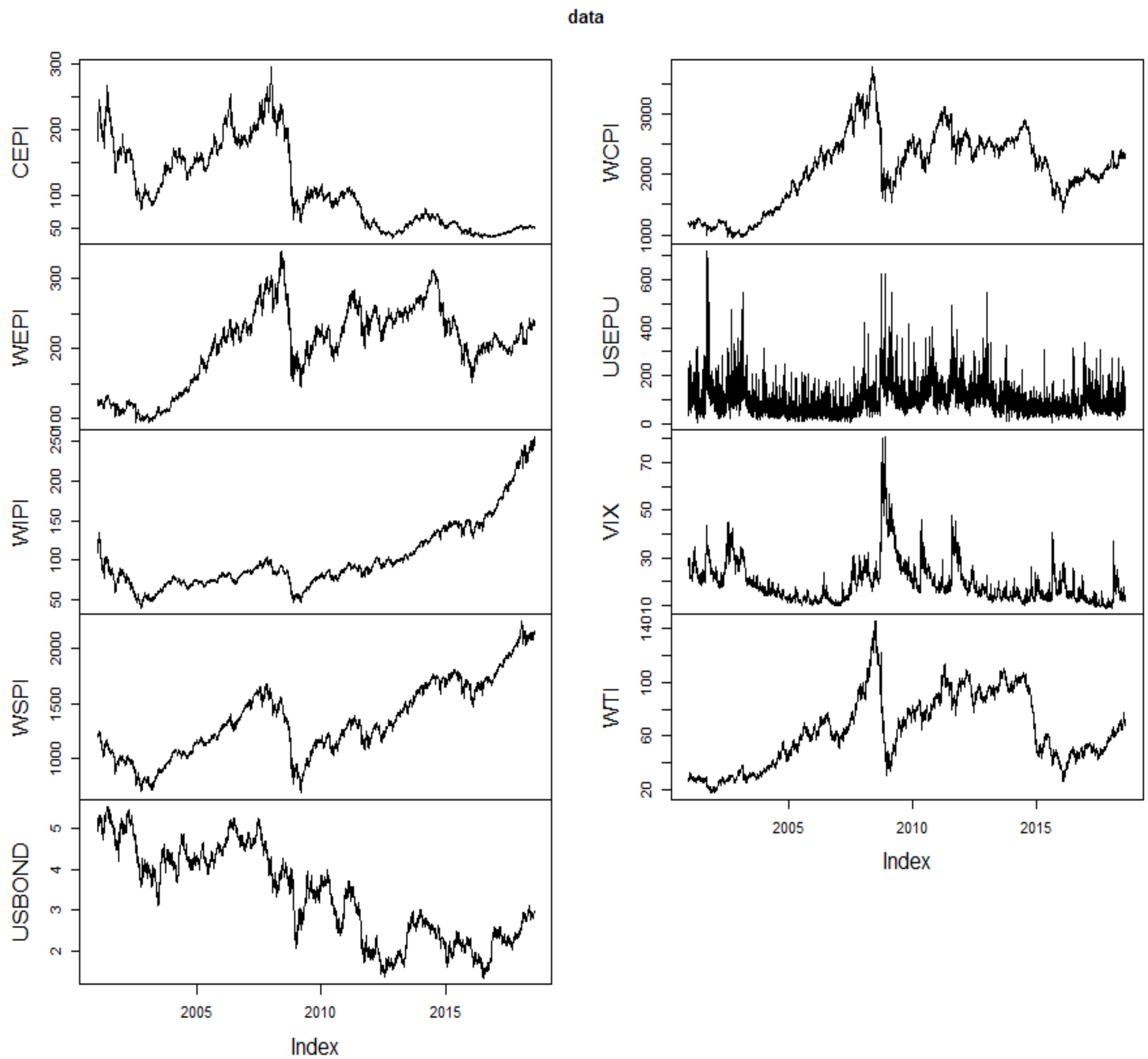
Appendix

Figure A: Time Series Plot of Level Data Series



Note: CEPI (WilderHill Clean Energy Price Index); (WEPI) MSCI World Energy Price Index), WIPI (MSCI World IT Price Index); WSPI (MSCI World Stock Price Index); WCPI (MSCI World Commodity Producers Index) VIX (VIX index); USEPU (US Economic Policy Uncertainty Index); USBOND (US Treasury Benchmark Bond 10 Years (DS) - Red. Yield) and WTI (West Texas Intermediate).

Table A: Descriptive Statistics

	CEPI	WEPI	WIPI	WSPI	USBOND	WCPI	USEPU	VIX	WTI
Mean	-0.029	0.014	0.016	0.012	-0.012	0.014	0.011	-0.016	0.022
Variance	3.897	2.048	1.868	0.99	3.721	1.881	3295.762	45.864	5.579
Skewness	-0.257***	-0.522***	0.068*	-0.397***	-0.015	-0.521***	0.023	0.990***	-0.089**
Kurtosis	4.728***	9.635***	5.779***	8.534***	3.570***	9.948***	1.327***	7.647***	4.558***
JB	4323.886***	17954.673***	6386.976***	14041.953***	2436.560***	19127.999***	336.899***	11927.433***	3977.214***
ERS	-8.063***	-14.146***	-3.779***	-19.975***	-19.933***	-16.219***	-1.498	-19.243***	-3.983***
Q(20)	27.570***	64.649***	36.486***	94.689***	19.420**	108.270***	782.553***	71.807***	31.496***
Q2(20)	1423.667***	2037.256***	328.976***	1689.307***	4.25	2408.324***	152.653***	3.262	285.421***
LM(20)	901.201***	1316.929***	621.187***	1234.432***	260.265***	1432.483***	37.381***	97.125***	420.632***

Notes: (1)CEPI (WilderHill Clean Energy Price Index); (WEPI) MSCI World Energy Price Index), WIPI (MSCI World IT Price Index); WSPI (MSCI World Stock Price Index); WCPI (MSCI World Commodity Producers Index) VIX (VIX index); USEPU (US Economic Policy Uncertainty Index); USBOND (US Treasury Benchmark Bond 10 Years (DS) - Red. Yield) and WTI (West Texas Intermediate). (2)* denotes significant at 1% level of significance. (3) JB is the Jarque and Bera normality test; ERS is the Elliott, Rothenberg and Stock modified ADF test for unit root; Q(20)and $Q^2(20)$ are the Ljung–Box test statistics; LM (20) is the Lagrange Multiplier test for serial correlation.

Table B: Correlation Matrix

	CEPI	WEPI	WIPI	WSPI	USBOND	WCPI	USEPU	VIX	WTI
CEPI	1	0.637	0.731	0.753	0.317	0.638	0	-0.595	0.264
WEPI	0.637	1	0.541	0.803	0.325	0.972	0.002	-0.534	0.521
WIPI	0.731	0.541	1	0.821	0.32	0.554	-0.009	-0.62	0.164
WSPI	0.753	0.803	0.821	1	0.368	0.837	-0.003	-0.664	0.299
USBOND	0.317	0.325	0.32	0.368	1	0.318	0.013	-0.303	0.213
WCPI	0.638	0.972	0.554	0.837	0.318	1	0.001	-0.518	0.496
USEPU	0	0.002	-0.009	-0.003	0.013	0.001	1	0.004	0.012
VIX	-0.595	-0.534	-0.62	-0.664	-0.303	-0.518	0.004	1	-0.181
WTI	0.264	0.521	0.164	0.299	0.213	0.496	0.012	-0.181	1

Note: CEPI (WilderHill Clean Energy Price Index); (WEPI) MSCI World Energy Price Index), WIPI (MSCI World IT Price Index); WSPI (MSCI World Stock Price Index); WCPI (MSCI World Commodity Producers Index) VIX (VIX index); USEPU (US Economic Policy Uncertainty Index); USBOND (US Treasury Benchmark Bond 10 Years (DS) - Red. Yield) and WTI (West Texas Intermediate).

Table C: Portfolio Weights and Hedge ratios (long/short) Summary Statistics

	Full Sample				**Pre-Financial Crisis**				**Financial Crisis**				**Post Financial Crisis**			
	Panel B: Portfolio weights (WTI/Company j)															
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
WTI CEPI	0.374048	0.183725	0	0.919376	0.341838	0.18119	0	0.834109	0.373167	0.139939	0.146874	0.793369	0.31307	0.160685	0.118097	0.607533
WTI WEPI	0.154291	0.154769	0	0.921635	0.142414	0.160999	0	0.841409	0.196626	0.111599	0.013751	0.545851	0.073008	0.064515	0	0.181947
WTI WIPI	0.199209	0.181749	0	0.91483	0.350881	0.255722	0	0.914829	0.146712	0.077571	0.028953	0.375998	0.117832	0.084928	0.027438	0.276993
WTI WSPI	0.100886	0.12082	0	0.752833	0.108838	0.146691	0	0.752833	0.078441	0.065513	0.00844	0.356198	0.076482	0.086325	0.004955	0.245558
WTI USBOND	0.399907	0.19841	0.008032	0.961648	0.278769	0.129978	0.008032	0.65529	0.249919	0.054502	0.088736	0.366433	0.228998	0.068854	0.12871	0.343895
WTI WCPI	0.152487	0.156977	0	0.904484	0.121488	0.145119	0	0.794883	0.176053	0.107785	0.03396	0.575151	0.0877	0.096256	0	0.286024
WTI USEPU	0.99763	0.004754	0.948938	1	0.998714	0.001859	0.990021	1	0.999471	0.000736	0.996645	1	1	0	1	1
WTI VIX	0.918612	0.095846	0.185507	1	0.874842	0.093277	0.378385	1	0.937372	0.034225	0.812285	0.998952	0.93099	0.044492	0.837493	0.993094
CEPI WEPI	0.239822	0.162701	0	0.831761	0.240291	0.145464	0	0.831761	0.295733	0.149016	0.030654	0.669159	0.261342	0.165612	0	0.522658
CEPI WIPI	0.193798	0.273227	0	1	0.527425	0.314373	0	1	0.069524	0.062097	0	0.49098	0.031243	0.037176	0	0.114565
CEPI WSPI	0.030908	0.082106	0	0.83738	0.056806	0.112033	0	0.699042	0.001955	0.009448	0	0.077417	0	0	0	0
CEPI USBOND	0.517298	0.209578	0	0.981858	0.421093	0.157152	0.077114	0.84035	0.360836	0.094959	0.118662	0.550128	0.342319	0.122758	0.096232	0.488394
CEPI WCPI	0.212476	0.154251	0	0.802005	0.181165	0.122753	0	0.802005	0.236296	0.125231	0	0.601822	0.232384	0.141498	0.017359	0.52473
CEPI USEPU	0.997543	0.005668	0.934515	1	0.999317	0.001021	0.992599	1	0.999176	0.000835	0.996705	1	0.998273	0.001007	0.996011	0.999745
CEPI VIX	0.988251	0.062368	0.261154	1	0.99071	0.026823	0.795024	1	1	0	1	1	1	0	1	1
WEPI WIPI	0.435019	0.242083	0	1	0.727422	0.208671	0.247159	1	0.3077	0.129327	0.063523	0.7088	0.375696	0.113223	0.186157	0.565479
WEPI WSPI	0.147988	0.168419	0	0.945258	0.278096	0.203956	0	0.945258	0.076264	0.083228	0	0.382746	0.17399	0.170226	0.013782	0.512794
WEPI USBOND	0.699446	0.188583	0	1	0.645544	0.153417	0.062527	0.90455	0.50392	0.107774	0.269018	0.727053	0.550662	0.068397	0.409158	0.650371
WEPI WCPI	0.281674	0.356259	0	1	0.070153	0.163769	0	0.922134	0.192467	0.275559	0	1	0.345963	0.396781	0	1
WEPI USEPU	0.998294	0.00475	0.943654	1	0.999062	0.001148	0.990303	1	0.999932	0.000197	0.998747	1	0.999861	0.000346	0.998821	1
WEPI VIX	0.99522	0.031286	0.498133	1	0.995031	0.020235	0.818444	1	0.999942	0.000657	0.989577	1	1	0	1	1
WIPI WSPI	0.16499	0.244762	0	1	0.018547	0.064373	0	0.625765	0.116542	0.151167	0	0.715898	0.129435	0.131177	0	0.413533
WIPI USBOND	0.714657	0.250309	0.010817	1	0.4352	0.262416	0.010817	0.865639	0.686049	0.100822	0.431786	0.843394	0.697159	0.089042	0.457021	0.789195
WIPI WCPI	0.530737	0.254497	0	1	0.226186	0.198977	0	0.747146	0.644837	0.142512	0.223556	0.902456	0.620379	0.083838	0.520888	0.821294

WIPI USEPU	0.998681	0.002846	0.969467	1	0.999348	0.00147	0.990067	1	0.999067	0.000531	0.997626	1	0.998916	0.000653	0.997404	0.999788
WIPI VIX	0.992902	0.032473	0.549854	1	0.972519	0.05939	0.549854	1	1	0	1	1	1	0	1	1
WSPI USBOND	0.855446	0.162616	0.079558	1	0.772011	0.184179	0.097778	0.968691	0.815666	0.109977	0.414593	0.950596	0.828252	0.128315	0.557899	0.940831
WSPI WCPI	0.837919	0.200438	0	1	0.651479	0.244599	0	1	0.929627	0.101194	0.56714	1	0.886567	0.112899	0.689186	1
WSPI USEPU	0.998612	0.002997	0.967589	1	0.99958	0.000567	0.995448	1	0.999421	0.000467	0.998112	1	0.99889	0.000838	0.997216	0.99998
WSPI VIX	0.999985	0.000731	0.956754	1	1	0	1	1	1	0	1	1	1	0	1	1
USBOND WCPI	0.274441	0.184754	0	0.994879	0.297254	0.146049	0.066109	0.933991	0.45083	0.116787	0.218305	0.746892	0.436459	0.090303	0.271341	0.596087
USBOND USEPU	0.995562	0.004461	0.966443	1	0.998225	0.00159	0.992418	1	0.99697	0.001728	0.991778	0.999864	0.995697	0.001622	0.992246	0.99841
USBOND VIX	0.962001	0.062319	0.451798	1	0.976465	0.030062	0.851092	1	0.996451	0.006018	0.978512	1	1	0	1	1
WCPI USEPU	0.998159	0.004776	0.942026	1	0.999152	0.001058	0.991132	1	0.999826	0.000311	0.998665	1	0.999678	0.000445	0.99871	1
WCPI VIX	0.995438	0.030357	0.525633	1	0.998091	0.00885	0.901979	1	0.999987	0.000142	0.997866	1	0.999905	0.000562	0.996131	1
USEPU VIX	0.022348	0.023225	0	0.422588	0.014709	0.007268	0.001489	0.092895	0.017418	0.008738	0.002196	0.059964	0.025523	0.031601	0	0.101124
	Full Sample				**Pre-Financial Crisis**				**Financial Crisis**				**Post Financial Crisis**			
Panel A: Hedge ratios (long/short)																
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
NA		NA		NA												
CEPI WTI	2.52E-01	0.166481	-0.02518	1.101957	0.191896	0.164117	-0.02518	1.101957	0.168432	0.060221	7.15E-02	3.60E-01	2.27E-01	0.117161	3.77E-02	3.95E-01
WEPI WTI	6.44E-01	0.248758	0.077395	1.64539	0.525515	0.252157	0.077395	1.596334	0.50808	0.15169	2.26E-01	8.67E-01	7.84E-01	0.193195	4.80E-01	1.15E+00
WIPI WTI	3.83E-01	0.232885	-0.18063	1.738435	0.257594	0.207994	-0.18063	1.174832	0.209833	0.151276	-1.59E-01	5.88E-01	3.72E-01	0.223246	3.59E-02	7.31E-01
WSPI WTI	5.57E-01	0.291576	-0.08003	2.104103	0.488327	0.27995	-0.02435	1.704926	0.349419	0.21751	-8.00E-02	9.13E-01	5.13E-01	0.273183	6.48E-02	8.87E-01
USBOND WTI	1.62E-01	0.146955	-0.15795	0.921054	0.142725	0.153427	-0.15795	0.874245	0.142251	0.085166	-1.95E-02	3.51E-01	6.73E-02	0.089301	-6.83E-02	2.25E-01
WCPI WTI	6.11E-01	0.269959	0.067707	1.731595	0.502418	0.286128	0.067707	1.663078	0.458974	0.149111	1.58E-01	7.67E-01	7.50E-01	0.256353	3.41E-01	1.22E+00
USEPU WTI	5.69E-04	0.00295	-0.01876	0.017745	0.001766	0.002978	-0.00539	0.017745	0.001196	0.001623	-2.11E-03	5.54E-03	3.90E-03	0.001473	1.83E-03	7.61E-03
VIX WTI	5.76E-02	0.052331	-0.00672	0.512414	0.041738	0.022677	-0.00672	0.176515	0.031707	0.019129	-2.57E-03	7.58E-02	4.41E-02	0.031829	-4.45E-03	9.20E-02
WTI CEPI	1.60E-01	0.127858	-0.04267	0.80881	0.093034	0.069791	-0.04267	0.379568	0.106822	0.042682	3.19E-02	2.30E-01	9.44E-02	0.036203	4.80E-02	2.03E-01
WEPI CEPI	5.97E-01	0.216162	0.114165	1.322724	0.481021	0.168127	0.114165	1.317279	0.489059	0.188389	2.13E-01	9.37E-01	5.49E-01	0.247634	3.12E-01	1.01E+00
WIPI CEPI	8.49E-01	0.282913	0.206817	1.844765	0.542445	0.170536	0.206817	1.1653	0.857468	0.144178	4.89E-01	1.26E+00	1.02E+00	0.168369	8.00E-01	1.35E+00
WSPI CEPI	1.14E+00	0.263151	0.441059	2.427506	1.06798	0.327532	0.50364	2.427506	1.199808	0.151323	8.35E-01	1.68E+00	1.30E+00	0.093781	1.09E+00	1.49E+00
USBOND CEPI	2.14E-01	0.142968	-0.06724	1.097695	0.210385	0.129039	-0.01293	0.685329	0.147148	0.068616	-6.72E-02	2.82E-01	3.56E-01	0.13872	1.40E-01	6.99E-01
WCPI CEPI	6.29E-01	0.201061	0.194509	1.365429	0.565376	0.170403	0.194509	1.365429	0.547457	0.183606	2.10E-01	1.02E+00	5.57E-01	0.217216	3.14E-01	9.53E-01

USEPU CEPI	-4.24E-04	0.003484	-0.02677	0.0157	0.001198	0.002154	-0.00336	0.008925	0.000381	0.001919	-2.72E-03	6.11E-03	-1.06E-03	0.000678	-2.72E-03	-5.94E-05
VIX CEPI	1.22E-01	0.076818	0.017308	0.729853	0.113689	0.047797	0.042589	0.306898	0.096424	0.020595	4.64E-02	1.74E-01	9.23E-02	0.014356	5.53E-02	1.25E-01
WTI WEPI	2.05E-01	0.106875	0.031502	0.80839	0.113584	0.059809	0.031502	0.392585	0.180216	0.050071	8.33E-02	3.38E-01	1.96E-01	0.032172	1.42E-01	2.73E-01
CEPI WEPI	3.00E-01	0.11807	0.054183	0.762319	0.205581	0.079804	0.054183	0.602389	0.269506	0.061851	9.78E-02	4.63E-01	2.63E-01	0.03551	2.21E-01	3.55E-01
WIPI WEPI	4.53E-01	0.216455	0.043342	1.129014	0.191799	0.087719	0.043342	0.505414	0.371198	0.096897	1.58E-01	7.57E-01	3.18E-01	0.061197	2.24E-01	4.19E-01
WSPI WEPI	8.47E-01	0.2036	0.182492	1.536925	0.64004	0.176009	0.182492	1.212217	0.870854	0.181018	5.21E-01	1.40E+00	7.51E-01	0.125536	5.61E-01	9.41E-01
USBOND WEPI	1.35E-01	0.117721	-0.10142	1.001085	0.107579	0.088513	-0.0217	0.50192	0.023187	0.047789	-1.01E-01	1.40E-01	1.13E-01	0.045325	4.12E-02	2.36E-01
WCPI WEPI	9.89E-01	0.094243	0.711717	1.437482	1.051245	0.085988	0.834273	1.437482	1.01298	0.098505	8.23E-01	1.27E+00	9.56E-01	0.093837	7.64E-01	1.09E+00
USEPU WEPI	-3.23E-04	0.002936	-0.02717	0.007694	-0.0001	0.0013	-0.00423	0.004239	0.001586	0.001399	-9.35E-04	5.18E-03	9.49E-04	0.000883	-8.50E-04	2.38E-03
VIX WEPI	7.42E-02	0.056889	0.006927	0.556272	0.058322	0.031793	0.006927	0.22129	0.05526	0.014444	2.70E-02	9.58E-02	4.75E-02	0.010979	2.24E-02	6.48E-02
WTI WIPI	1.12E-01	0.080771	-0.01827	0.5373	0.12971	0.09178	-0.0101	0.5373	0.044868	0.035097	-1.58E-02	1.53E-01	5.25E-02	0.024604	5.92E-03	1.07E-01
CEPI WIPI	3.97E-01	0.187234	0.106134	1.260375	0.572931	0.262992	0.161239	1.260375	0.268009	0.073529	1.06E-01	4.80E-01	3.39E-01	0.015567	3.09E-01	3.73E-01
WEPI WIPI	4.03E-01	0.209847	0.062059	1.974164	0.497226	0.332976	0.086654	1.974164	0.203284	0.072943	6.21E-02	3.76E-01	2.26E-01	0.11436	1.08E-01	4.28E-01
WSPI WIPI	1.08E+00	0.422389	0.500339	3.321521	1.547515	0.567883	0.544735	3.321521	0.934734	0.152164	5.33E-01	1.28E+00	9.19E-01	0.075275	7.69E-01	1.06E+00
USBOND WIPI	1.75E-01	0.134926	0.016935	0.951989	0.266723	0.193188	0.024885	0.951989	0.118753	0.03632	2.96E-02	2.05E-01	2.36E-01	0.076074	1.22E-01	4.41E-01
WCPI WIPI	4.23E-01	0.220005	0.084086	1.91144	0.563008	0.340209	0.099489	1.91144	0.244501	0.084408	8.41E-02	4.28E-01	2.51E-01	0.094044	1.33E-01	4.17E-01
USEPU WIPI	6.33E-07	0.002729	-0.01941	0.011717	0.00215	0.002786	-0.00568	0.011717	-0.00071	0.000579	-2.18E-03	1.02E-03	-8.62E-04	0.000589	-2.23E-03	-9.62E-06
VIX WIPI	9.74E-02	0.061806	0.02014	0.433968	0.128908	0.078128	0.026648	0.428353	0.066251	0.015881	2.65E-02	1.13E-01	5.80E-02	0.011635	2.80E-02	7.61E-02
WTI WSPI	9.01E-02	0.077763	-0.01376	0.569001	0.056074	0.031689	-0.01376	0.215698	0.039385	0.025612	-6.02E-03	1.00E-01	3.97E-02	0.018277	1.90E-02	8.94E-02
CEPI WSPI	2.80E-01	0.105623	0.056367	0.8025	0.273303	0.126457	0.056367	0.707559	0.205178	0.045704	1.17E-01	3.47E-01	2.53E-01	0.046434	1.88E-01	3.35E-01
WEPI WSPI	4.16E-01	0.149373	0.090622	0.928616	0.375476	0.134281	0.093212	0.85827	0.259487	0.080062	1.47E-01	4.96E-01	3.03E-01	0.146214	1.61E-01	5.82E-01
WIPI WSPI	5.55E-01	0.172596	0.150553	1.213245	0.371339	0.109462	0.150553	0.672286	0.512187	0.061132	3.72E-01	7.42E-01	5.34E-01	0.110329	3.82E-01	7.03E-01
USBOND WSPI	1.39E-01	0.103954	0.014543	0.811016	0.139051	0.112174	0.014543	0.637196	0.098198	0.022933	5.11E-02	1.79E-01	1.78E-01	0.061235	1.21E-01	3.70E-01
WCPI WSPI	4.74E-01	0.143683	0.134953	1.05338	0.474483	0.149503	0.174838	1.05338	0.337474	0.090705	1.87E-01	6.13E-01	3.67E-01	0.133492	1.93E-01	5.98E-01
USEPU WSPI	-7.14E-04	0.002128	-0.01809	0.005661	0.000222	0.001026	-0.00221	0.005661	-0.0004	0.000615	-1.78E-03	1.17E-03	-9.71E-04	0.00076	-2.43E-03	5.91E-06
VIX WSPI	7.52E-02	0.048992	0.015507	0.441844	0.076127	0.040846	0.020852	0.277099	0.051064	0.010759	2.56E-02	8.46E-02	4.56E-02	0.007069	2.79E-02	6.30E-02
WTI USBOND	1.19E-01	0.11992	-0.09212	0.780428	0.05798	0.060714	-0.09212	0.274509	0.058059	0.045655	-5.42E-03	1.85E-01	2.12E-02	0.026885	-1.94E-02	8.39E-02
CEPI USBOND	2.36E-01	0.153162	-0.06161	0.870476	0.162908	0.102634	-0.00241	0.518673	0.098366	0.052143	-1.08E-02	2.02E-01	2.08E-01	0.038742	1.34E-01	2.90E-01
WEPI USBOND	3.07E-01	0.236706	-0.05968	1.122366	0.168596	0.111591	-0.03659	0.599741	0.034297	0.052148	-5.97E-02	1.72E-01	1.39E-01	0.063348	5.77E-02	2.45E-01

WIPI USBOND	4.12E-01	0.256727	0.015436	1.438476	0.199837	0.117814	0.015436	0.5351	0.252236	0.122218	2.87E-02	5.03E-01	4.16E-01	0.05332	3.08E-01	5.46E-01
WSPI USBOND	6.03E-01	0.340341	0.06413	2.06176	0.36999	0.158018	0.066967	0.835123	0.367844	0.14887	6.41E-02	7.12E-01	5.61E-01	0.123272	3.36E-01	7.28E-01
WCPI USBOND	3.30E-01	0.242515	-0.08023	1.27811	0.20657	0.129705	-0.08023	0.673956	0.051831	0.057703	-4.02E-02	2.39E-01	1.65E-01	0.048874	8.93E-02	2.48E-01
USEPU USBOND	-2.69E-03	0.003077	-0.01651	0.006804	-0.00083	0.001676	-0.00546	0.00411	-0.0027	0.001735	-7.80E-03	4.23E-04	-4.03E-03	0.001516	-7.32E-03	-1.74E-03
VIX USBOND	6.89E-02	0.048388	-0.00379	0.325088	0.0445	0.0235	-0.00379	0.122092	0.03562	0.015761	5.41E-03	6.34E-02	4.58E-02	0.014586	1.51E-02	6.42E-02
WTI WCPI	1.78E-01	0.108255	0.007769	0.768408	0.085873	0.049997	0.007769	0.332224	0.135564	0.043656	4.89E-02	2.94E-01	1.71E-01	0.031319	1.14E-01	2.52E-01
CEPI WCPI	2.90E-01	0.120065	0.046585	0.754407	0.194441	0.07341	0.050411	0.576389	0.256285	0.062474	8.83E-02	4.66E-01	2.58E-01	0.036053	2.11E-01	3.35E-01
WEPI WCPI	8.84E-01	0.085066	0.624693	1.240775	0.833593	0.059272	0.624693	0.98767	0.844392	0.072656	6.90E-01	1.04E+00	9.04E-01	0.098318	7.63E-01	1.13E+00
WIPI WCPI	4.32E-01	0.215903	0.03844	1.169648	0.179783	0.085467	0.03844	0.468942	0.374855	0.102316	1.49E-01	7.56E-01	3.52E-01	0.085609	2.47E-01	4.88E-01
WSPI WCPI	8.82E-01	0.215073	0.195213	1.458126	0.653055	0.186038	0.195213	1.118598	0.948894	0.16719	6.15E-01	1.40E+00	8.88E-01	0.121215	6.65E-01	1.13E+00
USBOND WCPI	1.33E-01	0.112769	-0.0612	0.970661	0.101775	0.080421	-0.02098	0.512906	0.032587	0.037357	-6.12E-02	1.04E-01	1.34E-01	0.053356	6.38E-02	3.01E-01
USEPU WCPI	-6.29E-04	0.002895	-0.02704	0.006855	-0.00024	0.001088	-0.00442	0.003515	0.000974	0.001273	-1.05E-03	4.78E-03	4.54E-04	0.000865	-1.05E-03	1.97E-03
VIX WCPI	6.72E-02	0.053023	0.005571	0.526264	0.052562	0.02628	0.011823	0.205538	0.047381	0.012442	2.13E-02	8.39E-02	4.43E-02	0.008329	2.72E-02	6.07E-02
WTI USEPU	4.97E-01	1.583243	-5.43174	13.37307	0.798895	1.507069	-3.66784	5.270622	1.029507	1.679774	-2.20E+00	5.45E+00	3.16E+00	0.745484	2.16E+00	4.90E+00
CEPI USEPU	-2.64E-01	2.190369	-15.6367	12.06287	0.850216	2.168533	-7.30546	7.787308	-0.41333	2.72098	-9.50E+00	8.59E+00	-1.60E+00	0.828027	-5.01E+00	-3.03E-01
WEPI USEPU	1.96E-01	3.492711	-14.7076	20.34146	-0.71867	3.643488	-14.7076	10.23779	3.95004	2.922857	-3.25E+00	1.73E+01	3.37E+00	3.218505	-2.64E+00	1.15E+01
WIPI USEPU	-5.85E-01	4.015043	-21.4354	19.21439	2.380495	3.183989	-9.76265	19.21439	-4.88481	4.52742	-2.14E+01	4.90E+00	-4.00E+00	2.047145	-1.12E+01	-4.76E-02
WSPI USEPU	-2.47E+00	5.506979	-33.2728	20.16541	-0.2519	4.873578	-23.0573	12.8393	-6.45268	7.675456	-2.78E+01	9.76E+00	-6.58E+00	3.275961	-1.92E+01	2.31E-01
USBOND USEPU	-2.51E+00	3.568826	-28.9824	9.031943	-1.48001	3.067521	-15.5756	9.031943	-8.55381	5.77227	-2.90E+01	7.57E-01	-1.10E+01	3.245724	-1.81E+01	-4.95E+00
WCPI USEPU	-4.52E-01	3.449647	-15.675	18.2519	-1.14056	3.558598	-15.3709	8.299202	2.346956	3.581187	-6.20E+00	1.83E+01	1.87E+00	3.40959	-4.33E+00	1.00E+01
VIX USEPU	-2.34E-01	0.518097	-4.1896	1.708321	-0.28236	0.418585	-2.50038	0.747969	-0.68531	0.699662	-2.82E+00	7.73E-01	1.51E-01	0.592302	-3.87E-01	1.71E+00
WTI VIX	4.98E-01	0.372216	-0.32812	4.306252	0.276385	0.153547	-0.04364	1.144695	0.336285	0.202666	-9.95E-02	9.70E-01	2.60E-01	0.299508	-3.28E-01	6.84E-01
CEPI VIX	1.79E+00	0.83409	0.380446	12.21838	1.358165	0.41573	0.380446	3.681289	1.780981	0.374902	1.02E+00	3.49E+00	2.71E+00	1.593251	1.52E+00	8.19E+00
WEPI VIX	2.15E+00	1.055723	0.168226	11.64831	1.673455	0.555664	0.168226	3.697511	1.7921	0.595943	8.92E-01	4.39E+00	3.16E+00	2.827228	1.04E+00	1.14E+01
WIPI VIX	3.28E+00	1.692783	0.460314	16.26077	1.548994	0.883213	0.460314	5.018877	3.971225	0.855697	2.45E+00	9.02E+00	4.91E+00	2.562877	2.79E+00	1.32E+01
WSPI VIX	4.69E+00	2.065938	0.945805	17.56091	3.684034	1.304392	1.091672	8.769792	5.547438	0.896043	3.94E+00	1.15E+01	6.64E+00	2.933086	4.33E+00	1.68E+01
USBOND VIX	9.32E-01	0.615942	-0.02963	9.03174	0.743011	0.328041	-0.02963	1.961703	1.0608	0.382839	2.96E-01	2.70E+00	2.14E+00	1.511258	1.06E+00	7.88E+00
WCPI VIX	2.14E+00	1.006896	0.432811	11.01857	1.879653	0.55474	0.432811	4.26493	1.843546	0.591613	9.65E-01	3.89E+00	3.09E+00	2.63924	9.40E-01	1.10E+01
USEPU VIX	-3.11E-03	0.009727	-0.07678	0.091279	-0.00284	0.004505	-0.01985	0.017271	-0.00488	0.006565	-1.71E-02	2.07E-02	-1.83E-03	0.007649	-1.63E-02	1.00E-02