ESSAYS ON RISK MANAGEMENT MODELING WITH APPLICATIONS TO ENERGY MARKETS

A Thesis

by

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ABSTRACT

The dissertation consists of three essays, addressing different aspects of risk management in multi-commodity setting with application to energy markets.

The effectiveness of traditional and alternative hedging strategies during the period of volatile oil price is analyzed. Minimization of downside risk (LPM_2) and variance are used as alternative hedging objectives. The joint distribution of spot and futures price log returns is modeled using a kernel copula method. The results show that allowing for arbitrary proportions in the sizes of futures positions generally achieves a better hedging performance. The advantage becomes particularly important during periods characterized by greater variation of the cross-dependence between the price log returns of individual commodities. In addition, using LPM_2 as a hedging criterion can help hedgers to better track downside risk as well as lead to higher expected profit and lower expected shortfall.

The dynamics of WTI/Brent price spread is studied and how the spread responds to different types of physical market shocks is investigated. A test for structural breaks in the WTI/Brent price spread indicates a change from a stationary to a non-stationary time series in December 2010. The impact of physical market fundamentals on the dynamics of WTI/Brent price spread is then analyzed using a Structural Vector Autoregressive Model (SVAR). Impulse response functions generated from SVAR model show that the

WTI/Brent spread is mainly driven by the U.S. production and U.S. business activity shocks.

The dynamics of correlation structure and volatility transmission mechanism between crude oil futures and stock market at both aggregate and individual sector levels are analyzed. We find that the dynamic conditional correlation between crude oil and stock market increased sharply during the 2008-2009 financial crisis. Volatility spillover analysis show that Financials (XLF) and Technology (XLK) sectors are the two strongest volatility transmitters. The roles of crude oil and S&P500 index as transmitters or receivers is highly dependent on the market condition, namely, crude oil's volatility transmission impact is larger when its price is higher and S&P500 is more likely to be "receiving" volatility when the stock market is in crisis.

DEDICATION

To my grandparents.

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CHAPTER I.

INTRODUCTION

Because of oil's dominant role as an energy source, crude oil and its refined product markets are the most important commodity markets for industrialized economies. In recent years, major changes have been observed in the behavior of global oil markets. Between 2014 and 2016, WTI crude oil prices experienced a sharp decline, from over $100 per barrel to below $40 per barrel. The prices of refined products, such as gasoline and heating oil, also decreased by more than 50%. In addition, prices of WTI and Brent, which used to move closely together, started to diverge from 2010, creating potential risk as well as arbitrage opportunities. Outside of energy market, crude oil has also been suggested as an alternative investment to portfolio managers for diversification purpose due to its low correlation with equity market. However, the process of "commodity financialization" started in early 2000s has impacted the oil-equity linkage. The highly volatile oil prices and oil-equity relations expose oil market participants as well as portfolio managers to higher levels of risk and call for new risk management strategies.

Chapter II analyzes effectiveness of traditional and alternative hedging strategies during the period of volatile oil price. Optimal strategies are constructed for oil refineries for both 3:2:1 fixed ratio (traditional crack spread) hedging and arbitrary proportion hedging during the periods of relatively stable and volatile oil prices observed in recent years. Minimization of downside risk (LPM_2) and variance are used as alternative hedging objectives. The joint distribution of spot and futures price log returns is modeled using a kernel copula method. The hedging performance of the constructed strategies is compared using hedging effectiveness, expected profit, and expected shortfall. The results show that allowing for arbitrary proportions in the sizes of futures positions generally achieves a better hedging performance. The advantage becomes particularly important during periods characterized by greater variation of the cross-dependence between the price log returns of individual commodities. In addition, using LPM_2 as a hedging criterion can help hedgers to better track downside risk as well as lead to higher expected profit and lower expected shortfall.

Chapter III studies the dynamics of WTI/Brent price spread during the period between January 1994 and March 2016 and investigates how the spread responds to different types of physical market shocks. A test for structural breaks in the WTI/Brent price spread indicates a change from a stationary to a non-stationary time series in December 2010. The impact of physical market fundamentals on the dynamics of WTI/Brent price spread is then analyzed using a Structural Vector Autoregressive Model (SVAR) which reflects the response of WTI/Brent price spread to shocks in Norway Crude Oil Production, U.S. Crude Oil Production, PMI economic activity index, and Crude Oil Inventory in U.S. PADD2 . The SVAR model is estimated for each sub-sample period separated by the structural break. Impulse response functions show that the WTI/Brent spread is mainly driven by the U.S. production and U.S. business activity shocks.

Chapter IV analyzes the dynamics of correlation structure and volatility transmission mechanism between crude oil futures and stock market at both aggregate and individual sector levels. We find that the dynamic conditional correlation between crude oil and stock market increased sharply during the 2008-2009 financial crisis and remains at a higher level during the post-crisis period. Both rolling-window and static volatility spillover analysis show that Financials (XLF) and Technology (XLK) sectors are the two strongest volatility transmitters. The roles of crude oil and S&P500 index as transmitters or receivers is highly dependent on the market condition, namely, crude oil's volatility transmission impact is larger when its price is higher and S&P500 is more likely to be "receiving" volatility when the stock market is in crisis.

CHAPTER II.

IS HEDGING THE CRACK SPREAD NO LONGER ALL IT'S CRACKED UP TO BE?[1]

II.1. Introduction

Between 2014 and 2016, crude oil prices have exhibited unusual behavior, dropping from over $100 per barrel to below $40 per barrel in less than two years. During the same time period, prices of both gasoline and heating oil almost halved. Facing such drastic changes in both input and output prices, oil refineries are presented with challenging risk management decisions (Ederington et al., 2011; Kaminski, 2014).

A typical oil refinery's profit margin is tied directly to the price difference between crude oil and refined products, commonly called the crack spread. The most popular crack spread, which approximates the real-world output ratio from the refining process, adopts a 3:2:1 ratio, namely, three barrels of crude oil can be cracked into two barrels of gasoline and one barrel of heating oil (EIA, 2002). Oil refineries can reduce their risk exposures to volatile market prices by hedging the crack spread in the futures market. In 1994, NYMEX launched the crack spread contract, which bundles the purchase of three crude oil futures contract with the sale of two unleaded gasoline

[1] Reprinted from "Is hedging the crack spread no longer all it's cracked up to be?". Liu, P., Vedenov, D., & Power, G. J. (2017). Energy Economics, *63*, 31-40., Copyright (2017), with permission from Elsevier.

futures contract and one heating oil futures contract[2] (with delivery a month later) and makes them a single trade, thus lowering margin costs. A 3:2:1 crack spread futures position can also be created as a synthetic contract by directly trading futures on crude oil, gasolines and heating oil at a fixed 3:2:1 ratio. Even though the crack spread futures has a very low trading volume, the data show that the trading volume in the synthetic 3:2:1 crack spread is pretty high.

However, given the somewhat erratic behavior of spot prices in recent years, the question arises whether hedging individual commodities at a ratio other than 3:2:1 might be more effective. Indeed, Kaminski (2014) explains (p.S4) that: “This [3:2:1 ratio] wasn't a perfect hedge by any definition … The decoupling of the WTI [West Texas Intermediate] prices from the world prices reduced the efficiency of the 3:2:1 hedge and induced many hedgers to switch to Brent futures as the preferred hedging instrument…”. Yet, compared with hedging crude oil, hedging the crack spread has received much less attention in the literature (Mahringer and Prokopczuk, 2015).

In this paper we address the above question by constructing optimal hedging strategies for both cases (fixed 3:2:1 ratio and arbitrary proportions) during periods of both relatively stable and volatile oil prices. The hedging performance of the constructed strategies is compared using several criteria. The key finding of the paper is that allowing deviations from the fixed 3:2:1 ratio improves hedging performance regardless

[2] The heating oil contract traded on the New York Mercantile Exchange has been renamed ultra-low-sulfur-diesel (ULSD) futures after the 2013 April contract, but to keep the terminology and notation consistent, we will use the term heating oil (HO) when referring to both the heating oil contract before April 2013 and the ULSD contract after April 2013.

of the criterion used. Furthermore, it appears that the key factor affecting hedging effectiveness is the dependence structure between the spot and futures price log returns.

The rest of the paper is organized as follows. The second section discusses the relevant literature. The third section outlines the modeling methodology including the hedging framework, our approach to modeling the joint distribution of spot and futures price log returns, as well as risk measures used to evaluate hedging performance. Data and implementation details are presented in the fourth section, followed by the discussion of the results in the fifth section. The last section provides concluding remarks.

II.2. Literature Review

Commodity processing activities always involve multiple commodities and thus exposure to price risk on both the input and output side. Soybean crushers buy soybeans and sell soybean oil and soybean meal, ethanol manufacturing involves purchasing corn and selling ethanol and other output products, oil refineries crack crude oil into petroleum products, and so on. Therefore, commodity processors have to implement multi-commodity hedging strategies.

The literature on hedging has traditionally focused on single-commodity hedging, which does not take into account price co-movements between the input and output commodities. However, Haigh and Holt (2002) point out that the assumption of price independence is unreasonable and often leads to optimal hedge ratios that are different from those suggested by the multi-commodity hedging models in which the covariation between the input and output prices is explicitly accounted for (see also Fackler and McNew, 1994, and Peterson and Leuthold, 1987). Several recent papers discuss hedging in a multi-commodity setting. Manfredo, Garcia and Leuthold (2000) study the hedging problem for a typical soybean crushing complex. They find that incorporating a time-varying covariance matrix into the joint price modeling can improve hedging effectiveness. Efimova and Serletis (2014) and Tejeda and Goodwin (2014) examine, for energy and agricultural commodities respectively, the usefulness of dynamically evolving multivariate GARCH models of conditional volatility. Power and Vedenov (2010) and Power et al. (2013) analyze the multi-commodity hedging problem faced by a feedlot operator who buys feeder cattle and corn and sells fed cattle.

The authors suggest that incorporating the dependence structure between commodity prices into the hedging model leads to hedging behavior that is more consistent with the one observed in the marketplace.

The crack spread hedging problem for oil refineries has attracted interest in recent years, partly due to the highly volatile oil market. The North American oil production and refining market has undergone major changes in recent years. According to Kaminski (2014, p. S3) “[the] increase in production of crude in locations such as The Bakken and Eagle Ford, which were a few years ago of marginal importance to the US oil industry … collided with the existing transportation and refining infrastructure. Several congestion points emerged in the transportation grid and this, in turn, resulted in the breakdown of historical price relationships …”

Haigh and Holt (2002) show that accounting for time variation in the relationship between energy price series (crude oil, gasoline and heating oil) yields substantial rewards to hedgers in terms of risk reduction. Ji and Fan (2011) adopt a dynamic hedging approach for refineries and find that considering the interaction between different product markets as well as variation in price behavior over time can lead to a better multiproduct hedging strategy.

Various multivariate modeling methods as well as risk measures have been used to determine optimal hedging strategies and to analyze their performance. Variance of the effective net price or revenue continues to be the most commonly used measure of risk in the hedging literature, with variance minimization being the hedging objective. For example, Awudu et al. (2016) compare different hedging strategies for an ethanol producer using a Mean-VaR framework. However, looking at the crack spread Alexander, Prokopczuk and Sumawong (2013) find that variance-minimizing hedges offer no improvement in risk reduction. Indeed, Lien and Tse (2002) argue that a one-sided risk measure is closer to commodity hedgers' risk objective than the traditional variance measure. This is because upside and downside deviations are not equally undesirable in risk management. In that spirit, several recent papers use the second-order lower partial moment (LPM_2) as an alternative to variance (for example, Demirer and Lien, 2003; Turvey and Nayak, 2003; Mattos et al., 2008; Power and Vedenov, 2010).

Naturally, using different risk measures leads to different hedging strategies. Mattos et al. (2008) find that when transaction costs and alternative investments are introduced, the adoption of a downside risk measure with low reference levels can lead to hedge ratios that differ substantially from the minimum-variance hedge ratios. Power and Vedenov (2010) find that minimizing the LPM_2 measure results in smaller optimal hedge ratios compared to the minimum variance hedge. Furthermore, they suggest that the optimal hedge ratios implied by the downside risk criterion are more consistent with the behavior observed in the marketplace. In order to account for possibility of different hedging objectives, in this paper, we construct optimal hedging strategies using both variance minimization (MV) and LPM_2 minimization as hedging criteria.

Another important issue in the analysis of multi-commodity hedging is how to model the joint distribution of prices or returns. Multivariate normality of returns is often assumed for reasons of convenience. However, the distributions of spot and futures price log returns are known to deviate from normality (e.g. Ederington, 2011; Lai, 2015). Several methods have been suggested in the literature to circumvent this issue. For example, Manfredo et al. (2000) estimate a time-varying covariance matrix and a MGARCH(1,1) model with a constant correlation matrix. Power and Vedenov (2010) use a kernel copula approach to model the joint distribution of spot and futures price returns in a multi-commodity setting. The kernel copula methodology is nonparametric and imposes minimum assumptions about the underlying distribution. Tong et al. (2013) use thirteen parametric copula models with different underlying assumptions on the dependence structures to estimate the co-movement between crude oil and petroleum product prices. Power et al. (2013) propose a Nonparametric Copula-based Generalized Autoregressive Conditional Heteroskedastic (NPC-GARCH) dynamic hedging approach and find that it better captures lower tail risk than do other models such as GARCH-

DCC or GARCH-BEKK. In this paper, we follow Power and Vedenov (2010) and use a kernel copula approach to model the joint distribution of spot and futures price log returns. This allows us to move away from the multivariate normality assumption and better reproduce both the individual and joint behavior of price series.

The contribution of this paper can be described in the context of the prior literature. Although research on futures hedging is vast, there are notable gaps in the literature. First, in terms of methodology, little is known about how downside risk (LPM_2) extends to the case of several commodities, and in particular how jointly-estimated hedge ratios differ from the individual case. Studies that use LPM_2 focus on the case of a single commodity or asset, while those studies that do consider a multi-commodity setting tend to use instead minimum-variance (MV). Second, by far the most common criterion to judge hedging performance is Ederington's hedging effectiveness. However, experimental evidence and the positive empirical literature (e.g. Sanda et al. 2013)--based on actual hedger decisions--suggest that reducing tail risk may be a more appropriate yardstick by which to judge how well any given hedge performs. Third, little is known about the link between optimal hedge ratios, their effectiveness, and different market environments. This is worth investigating as during periods of market turmoil--such as higher price volatility, sharply dropping prices, or changes in dependence structures between related commodities--market participants may claim that futures are no longer effective hedging instruments (e.g. Kaminski, 2014). Fourth and last, relatively little research on futures hedging has been conducted specifically on the crack spread, yet this is an economically significant problem. Indeed, the question whether fixed futures positions are optimal could have important empirical and practical consequences. Our paper makes contributions along all four dimensions. The findings contribute new knowledge regarding downside risk hedging in a multi-commodity setting, showing how to implement such methods that could be extended to different settings. The paper also examines criteria other than variance minimization, and investigates the link between optimal hedge ratios, their effectiveness, and oil market conditions. Finally this study contributes new knowledge regarding how to best hedge the crack spread, in light of previous literature concluding that a naïve (1:1) hedge is sufficient.

II.3. Methodology

This section provides a general overview of the modelling approach and methodology used in the paper. Data and specific parameterization of all procedures are discussed in the following section.

II.3.1. Hedging Framework

We follow the conceptual framework suggested by Ji and Fan (2011) and assume a two-stage hedging cycle that covers three weeks (15 trading days) in total. The first stage is the planning stage that covers two weeks ($t - 3$ to $t - 1$). On the first day of the planning stage, the hedger (refinery) opens a long position in crude oil futures at F_{t-3}^{CL} and short positions in gasoline and heating oil futures at F_{t-3}^{RB} and F_{t-3}^{HO}, respectively[3]. The

[3] The superscripts CL, RB and HO correspond to the futures contract symbols as listed by the CME Group.

second stage is the operational stage which covers one week ($t-1$ to t). On the first day of the operational stage, the hedger buys crude oil on the spot market at S_{t-1}^{CL} to start the cracking process and concurrently closes the long position in crude oil at F_{t-1}^{CL}. On the last day of the operational stage (after the cracking process is finished), gasoline and heating oil are sold on the spot market at S_t^{RB} and S_t^{HO}, respectively, and the corresponding short positions are closed at F_t^{RB} and F_t^{HO}, respectively. In order to simplify the notation, in the rest of the section the subscript 0 is used to denote prices on the day when the hedge is set and the subscript 1 is used to denote prices on the day when the hedge position is liquidated. Assuming a 3:2:1 production ratio, the hedged crack margin per barrel of crude oil can be then written as

$$\pi(\boldsymbol{h}) = -S_1^{CL} + \frac{2}{3}S_1^{RB} + \frac{1}{3}S_1^{HO} + h^{CL}\left(F_1^{CL} - F_0^{CL}\right) + \frac{2}{3}h^{RB}(F_0^{RB} - F_1^{RB}) + \frac{1}{3}h^{HO}(F_0^{HO} - F_1^{HO}) \tag{1}$$

where $\pi(\boldsymbol{h})$ is the hedged crack profit, $\boldsymbol{h} = (h^{CL}, h^{RB}, h^{HO})$ is a vector of hedge ratios, $\{F_0^{CL}, F_0^{RB}, F_0^{HO}\}$ are observable initial futures prices, $\{S_1^{CL}, F_1^{CL}\}$ are spot and futures prices of crude oil 10 trading days ahead, and $\{S_1^{RB}, S_1^{HO}, F_1^{RB}, F_1^{HO}\}$ are spot and futures prices of gasoline and heating oil 15 trading days ahead, respectively.

Two scenarios are considered in the paper. In the first scenario, the refinery hedges the entire crack spread in the fixed 3:2:1 proportion implying $h^{CL} = h^{RB} = h^{HO} = h$ (single hedge ratio). In the second scenario, the refinery can hedge each of the three commodities individually, thus allowing for separate and not necessarily equal hedge ratios $\{h^{CL}, h^{RB}, h^{HO}\}$ (vector hedge ratio). No hedging corresponds to $h^{CL} = h^{RB} = h^{HO} = 0$.

II.3.2. Hedging Objectives

Generally, minimum variance (MV) is the most commonly used criterion to determine the optimal hedge ratio. The optimal hedge ratio calculated under the MV criterion is

$$h^{*} = \arg\min_{h} \mathrm{Var}(\pi(h)) \tag{2}$$

However, the fact that MV penalizes upside deviations and downside deviations equally is undesirable in risk management (e.g., Power and Vedenov, 2010). The LPM family is more suitable for the measurement of downside risk, which is of more interest for commodity hedgers. In particular, the second-order lower partial moment (LPM_2) has been increasingly used in the recent literature (Mattos et al., 2008; Power and Vedenov, 2010). The LPM_2 relative to a reference level $\bar{X}$ is defined as

$$LPM_2 = \int_{-\infty}^{\bar{X}} (\bar{X} - X)^2 dF(X) \tag{3}$$

where X is a random variable of interest and $F_X(X)$ is its cumulative distribution function.

For the hedging profit defined in (1), the reference level $\bar{\pi}$ can be set as the expected profit without hedging, i.e. $\bar{\pi} = E\pi(0)$. The optimal hedge ratio under the LPM_2 criterion can be then found as

$$\boldsymbol{h}^* = \arg\min_{\boldsymbol{h}} LPM_2(\boldsymbol{h}) = \arg\min_{\boldsymbol{h}} \int_{-\infty}^{\bar{\pi}} [\bar{\pi} - \pi(\boldsymbol{h})]^2 dF(\pi(\boldsymbol{h})) \tag{4}$$

II.3.3. The Joint Distribution of Spot and Futures Prices

The optimization problem in (4) does not have a closed-form solution, and therefore needs to be solved numerically. Monte Carlo simulation can be used to calculate the value of LPM_2 for any given vector of hedge ratios $\boldsymbol{h}$, and numerical optimization methods can be used to find the optimal hedge ratio $\boldsymbol{h}^*$.

In order to implement the Monte Carlo integration in (4), joint realizations of spot and futures prices $\{S_1^{CL}, S_1^{RB}, S_1^{HO}, F_1^{CL}, F_1^{RB}, F_1^{HO}\}$ in (1) need to be generated. The following approach is used to achieve this goal. First, we obtain log returns of historical spot and futures prices log returns $\{\varepsilon_1, \dots, \varepsilon_6\}$, where $\varepsilon_1 = \ln(S_1^{CL}) - \ln(S_0^{CL})$, $\varepsilon_2 = \ln(S_1^{RB}) - \ln(S_0^{RB})$, etc.[4]. The joint distribution of log returns is then modeled using the copula approach. The latter decomposes the joint distribution into a product of marginal distributions of individual variables and their dependence structure, or copula density (Cherubini, Luciano, and Vecciato, 2004).

Marginal probability density functions $f_1^{\varepsilon}(\cdot), \dots, f_6^{\varepsilon}(\cdot)$ are estimated using the kernel density method (Wand and Jones, 1995). The copula density $c(u_1, \dots, u_6)$ implied

[4] Note that the lags used for log-differencing correspond to the duration of the appropriate stages of the hedging cycle as described in Section II.3.1. Hedging Framework For example, ε_1 is obtained by log-differencing spot prices of crude oil two weeks apart, ε_2 is obtained by log-differencing spot prices of gasoline three weeks apart, and so on.

by the historical realizations of the log returns is estimated using the mirror image kernel approach (Charpentier, Fermanian, and Scaillet, 2007).

Next, N Monte Carlo draws $\{u_1^i, \ldots, u_6^i\}_{i=1}^N$ from the copula density are generated following the conditional sampling approach outlined in Cherubini, Luciano, and Vecciato (2004).[5] The generated draws are then transformed to draws from the joint distributions of log returns using the inverse marginal cumulative distribution functions. More specifically, for a given draw $u_j^i, i = 1, \ldots, N, j = 1, \ldots, 6$, from the copula density, the corresponding shock ε_j^i is found from the condition

$$u_j^i = \int_{-\infty}^{\varepsilon_j^i} f_j^{\varepsilon}(\epsilon) d\epsilon, \tag{5}$$

which can be solved numerically using standard numerical integration and root-finding methods (e.g. Miranda and Fackler, 2002).

Lastly, the generated log returns are used to construct realizations of final spot and futures prices by applying them to (known) initial observations of the same, e.g. $\{S_1^{CL}\}_i = S_0^{CL} \cdot \exp \varepsilon_1^i, i = 1, \ldots, N$, and so on. The constructed spot and futures prices can be used to calculate realizations $\{\pi^i(\boldsymbol{h})\}_{i=1}^N$ of net profit from hedging in (1) for any given vector of hedge ratios $\boldsymbol{h}$, and therefore determine the values of the hedging criteria in (2) and (4).

[5] Details about the value *N* are provided in section 4 on p.14. We use five years' worth of daily observations, but given the 250-day moving window, the sample for hedging analysis begins with observation 251.

II.3.4. Measures of Hedging Performance

In addition to the risk criteria used to determine the optimal hedge ratios (variance and LPM_2), we calculate three measures, namely hedging effectiveness, expected profit, and expected shortfall, which are commonly used in the literature to evaluate hedging performance.

Following Ederington (1979), hedging effectiveness is defined as the percentage reduction in risk criterion with hedging vs. without hedging. Specifically, the hedging effectiveness for minimum variance is determined as

$$HE_{MV} = 1 - \frac{\mathrm{Var}\big(\pi(\boldsymbol{h}^*)\big)}{\mathrm{Var}\big(\pi(0)\big)}. \tag{6}$$

Similarly, for LPM_2, hedging effectiveness can be determined as

$$HE_{\mathrm{LPM2}} = 1 - \frac{LPM_2\big(\pi(\boldsymbol{h}^*)\big)}{LPM_2\big(\pi(0)\big)}. \tag{7}$$

Expected profit is calculated by averaging calculated realizations of net profit from hedging $\{\pi^i(\boldsymbol{h})\}_{i=1}^N$ over the Monte Carlo draws, i.e.

$$E\pi = \frac{1}{N}\sum_{i=1}^{N} \pi^i(\boldsymbol{h}) \tag{8}$$

Expected shortfall (ES) at $\alpha = A\%$ level measures the expected profit or loss in the worst $A\%$ of the cases. The value of $\alpha = 5\%$ is used, as it is consistent with the related risk management literature on Value-at-risk (e.g., Jorion 2006). Expected shortfall belongs to the class of “coherent” risk measures (Acerbi and Tasche, 2002) and has been gaining popularity in financial risk management in recent years. For a continuous distribution with the probability density function $f(\cdot)$, the expected shortfall at the level α can be determined as

$$ES = -\frac{1}{\alpha}\int_{-\infty}^{x_\alpha} Xf(X)dX, \quad \text{where} \quad \alpha = \int_{-\infty}^{x_\alpha} f(X)dX. \tag{9}$$

II.4. Data and Implementation

In order to implement the methodology described in the previous section, we use the moving window approach. Specifically, for a given day in the data set, we treat the previous 250 observations relative to that day as "historical" data and treat the spot and futures prices on that day as the "initial" spot and futures prices observed by a hedger. We then calculate the realizations of price log returns based on the "historical" data, use those to generate 10,000 Monte Carlo draws of log returns as outlined in Section 3.3, and apply the latter to the "initial" spot and futures prices. Finally, the optimal hedge ratios in (2) and (4) are determined using numerical optimization methods.

Note that 250 trading days are approximately equal to one calendar year. Therefore, conceptually, we model a situation where on any given day a hedger uses one year's worth of historical data to estimate the distribution of the spot and futures prices at hedge liquidation and to determine the optimal hedge ratios that should be used to set up hedges on that day. The same steps are then repeated for all days for which data are available.[6]

For the purposes of analysis, daily spot and futures prices for crude oil, gasoline, and heating oil were obtained from Thomson Reuters Datastream for the period between January 2011 and December 2015. The spot price data that are used are West Texas Intermediate (WTI) crude oil at Cushing, Oklahoma, regular gasoline (unleaded) at New York Harbor, and for heating oil, Ultra Low Sulfur Diesel at New York Harbor. Futures prices were obtained for all contracts traded on any given day. Continuous futures prices series were then constructed by collating prices of nearby contracts and switching to the next delivery month at contract expiration.[7] Allowing for the 250-day length of the moving window, the optimal hedge ratios were calculated for each trading day between 1/2/2012 and 12/31/2015. Thus, we have N = 1044.

Spot and futures prices during this period are plotted in Figure A-1 and Figure A-2, respectively. The plots suggest that prices of all three commodities were relatively

[6] Since the first 250 observations are treated as "historical" data, the process effectively starts with the 251st observation in the sample.

[7] Collating futures series is necessary because true continuous time series of futures prices do not exist for these underlying assets. Indeed, each futures contract has a set expiry date, e.g. March 2015. In order to construct a continuous time series over a long period of time, we have to "splice" series from individual contracts. At any given date, the nearby futures contract is used. The nearby is the front-month futures, except near the end of the month, when we switch to the second contract. For example, the March 2015 futures contract expires on February 22, 2015. Thus, we use the March futures for all dates in February until the 23rd, at which date we start using the April futures. Lastly, to avoid a 'splicing bias', to compute the log return on February 23, we use the April futures price for both the current period and the previous period.

stable during 2012-2013 and the first half of 2014, sharply declined in the second half of 2014, and stabilized at a lower level during 2015.

The results of stationarity tests conducted on spot and futures prices and log returns for all three commodities are presented in Table B-1 This table shows that prices are nonstationary, while returns are stationary. In addition, a discrete Fourier transform was used to assess the existence of seasonality in log returns. There is insufficient evidence to support cyclical behavior in the series of log returns. Descriptive statistics of the data are reported in Table B-2 (separately for each year). The means of all series are close to zero during 2012-2013, and then become negative in 2014 and further in 2015. Variability is at its highest in 2014 and 2015, during which period prices are generally falling. Futures and spot price log returns are highly correlated during the entire period. Log returns for the three commodities are mostly left-skewed in 2012 and 2014, right-skewed in 2015, and mixed in 2013. Kurtosis for all log returns is around 3, except for 2014 when it increases substantially across commodities.

Log returns were calculated for each day in the dataset by log-differencing spot and futures prices with appropriate lags (two weeks for crude oil and three weeks for gasoline and heating oil, respectively, as explained in Section 3.1). Log returns for futures prices were first calculated separately for each contract and then a continuous series of log returns was constructed by collating series of log returns from nearby contracts and switching to the next contract month at expiration. This was done in order to avoid potential discontinuities due to differencing futures prices for different contracts.

II.5. Results

Variance-minimizing and LPM_2-minimizing hedge ratios were calculated for each trading day between January 1, 2012, and December 31, 2015, under two scenarios — a single hedge ratio used for all three commodities and separate hedge ratios (a vector hedge ratio) used for each individual commodity. The optimal hedge ratios implied by LPM_2 and MV criteria are plotted in Figure A-3 and Figure A-4, respectively.

The single hedge ratio (hedging the crack spread in the fixed 3:2:1 proportion) is relatively stable during the period considered, whether minimum-variance or LPM_2 is used. However, the vector hedge ratios (i.e., hedging individual commodities separately) show a lot of variation over time. Furthermore, hedge ratios for individual commodities often diverge from each other and deviate from the single hedge ratio, with the most pronounced deviations observed between October of 2012 and December of 2013 and between November of 2014 and December of 2015. The deviations are particularly dramatic for crude oil and heating oil, while the hedge ratio for gasoline tends to be more stable and closer to the single hedge ratio.

In particular, the negative hedge ratios for crude oil under LPM_2 from late 2014 through the first quarter of 2015 deserve further explanations. Multivariate hedge ratios describe futures positions that jointly allow for the minimization of a single risk criterion (e.g., variance or downside risk) to which contribute risks from each of the hedged commodities or assets. This means cross-commodity covariances matter, as do relative dollar value weights, which can lead to hedge ratios that are substantially different from individually estimated ratios (e.g., Fackler and McNew 1994). For downside risk in particular, prior research has shown that when hedging a commodity ‘crush’ or spread, one of the hedge ratios may be negative—a so-called ‘Texas hedge’ (e.g., Power and Vedenov, 2010). The economic intuition is that, given cross-covariances, it may be optimal to speculate in one commodity to minimize the overall risk for the ‘crush’ or spread.

The empirical results, consistent with theory, suggest that allowing for the separate hedging of individual commodities may lead to optimal hedges in proportions that are different from the conventional fixed-positions 3:2:1 crack spread. The choice of fixed 3:2:1 futures positions can be seen as a constrained case of the multivariate hedging problem. By definition, the constrained solution cannot improve on the unconstrained solution. Thus, it is to be expected that hedging each commodity individually should lead to a better hedging performance. That being said, it remains an empirical question to what extent the individual hedge ratios deviate from the single ratio, particularly under the LPM_2 objective. In order to confirm this, we calculate three measures of hedging performance, as discussed in Section 3.4, viz. hedging effectiveness, expected profit, and expected shortfall at 5%.

Reported in Table B-3, Table B-4 and Table B-5 are percent differences in each measure between the baseline case of using a single hedge ratio for all commodities, and the case where each commodity can be hedged separately[8]. The results show that relaxing the fixed 3:2:1 ratio in futures positions under the LPM_2 criterion leads to a

[8] For presentation purposes, the tables report the results as summarized by calendar year. Specific results for each day in the sample are available upon request.

clear improvement in hedging effectiveness, lower tail risk, and expected profit. To a lesser extent, this is also true under the M-V criterion. Although the economic magnitude is not always large, it is worth emphasizing that the improvement is across various possible states of nature (each window representing a different starting point). Interestingly, and to the point of this paper, improvements in hedging performance do not necessarily correspond to periods of higher volatility. The improvement in hedging effectiveness is lower during the period of falling prices in 2014, as the individually computed hedge ratios do not deviate much from the constrained, single hedge ratio. This result suggests that gains to more sophisticated hedging may be more limited during the most turbulent market periods. Fortunately, however, this also implies that most of the time, relaxing the fixed ratio will lead to improved risk management.

Hedging individual commodities always yields a higher hedging effectiveness compared to hedging the crack spread in the fixed 3:2:1 proportion, regardless of the criteria used (Table B-3). The improvement in hedging effectiveness is the greatest during 2013 and especially 2015. The periods during which the vector hedge ratios perform substantially better than the single hedge ratios are the same as when the vector hedge ratios deviate the most from single hedge ratios.

In terms of expected profit (Table B-4), the LPM_2-minimizing vector hedge ratio outperforms the corresponding single hedge ratio most of the time (992 out of overall 1044 windows, or 95.0%). The improvement is less pronounced under the minimum variance criterion (600 out of overall 1044 windows, or 57.5%). A possible explanation is that the minimum variance criterion equally penalizes upside and downside deviations from the mean, thus reducing expected profit. Regardless of the criteria, the advantage of the vector hedge ratio is once again at its most pronounced during 2013 and 2015.

Lastly, we compare the performance of both hedging strategies from the perspective of tail risk. Percent differences in expected shortfall at 5% are reported in Table B-5. Note that lower values of expected shortfall reflect lower tail risk, and therefore negative differences imply an improvement relative to the baseline. Once again, regardless of the criteria used, vector hedge ratios result in a better hedging performance most of the time (870 out of 1044 windows, or 83.3%, under LPM_2 and 748 out of 1044 windows, or 71.6% under MV), with the differences being most pronounced during 2013 and especially 2015. The improvement in hedging performance due to using vector hedge ratios is generally higher under the LPM_2 criterion. This result suggests that it is particularly useful to relax the fixed 3:2:1 ratio when the objective is to minimize downside risk.

A cursory comparison of Figure A-1, Figure A-2, Figure A-3 and Figure A-4 suggests that the performance of vector hedge ratios relative to a single hedge ratio does not seem to be clearly related to the dynamics of the changes in spot and futures prices. Indeed, the most substantial improvements in hedging performance are observed in 2013 and late 2014-2015. However, the first of these two periods is characterized by relatively stable levels of spot and futures prices, while the second is characterized by stabilization on the tail end of a steep decline of price series. On the other hand, during 2014, vector hedge ratios moved together and were close to the single hedge ratios despite a sharp decline in spot and futures prices.

In the single-commodity hedging case, the correlation between the changes in spot prices and changes in futures prices (over a period of time corresponding to the hedging period) is the key determinant of the optimal hedge ratio, at least in the case of variance minimization (e.g. Hull, 2009, p. 55). The evidence presented in Table B-1 and Table B-2 suggests that for the period considered, changes in spot and futures prices generally moved closely together, as seen in the reported correlations and Kendall's τ measures of dependence.

Therefore, we conjecture that, in the multi-commodity setting, cross-dependence between changes in prices of different commodities could matter. In order to verify this conjecture, Kendall's τ and Pearson correlation were used to measure the degree of dependence between the changes in futures prices of different commodities, as well as between the changes in spot prices across commodities. Kendall's τ measures rank dependence and is better suited at capturing tail dependence (e.g., Cherubini, Luciano, and Vecciato, 2004). More specifically, it is (with Spearman's rho) the most commonly used and most reliable measure of dependence for non-elliptical distributions (e.g., Embrechts, Lindskog, and McNeil, 2001). Thus, it is typically used to capture dependence in a copula framework, given that copulas are useful precisely when the distribution of interest may be non-elliptical. Given two vectors of data, *x* and *y*, and a number of observations *n*, we can compute Kendall's τ as follows:

$$\frac{\sum_{i<j}\left(sign(x_j - x_i) * sign(y_j - y_i)\right)}{n(n-1)/2} \tag{10}$$

Therefore, Kendall's τ appears to be a more appropriate measure to describe the behavior of LPM_2 hedge ratios. Pearson's correlation measures linear dependence, which is consistent with the underlying assumptions of the minimum variance method. Therefore, Pearson correlation seems appropriate to explain the behavior of the hedge ratios implied by the MV criterion. Both dependence measures were calculated for three pairs of futures price log return series using the same moving window approach as was used in calculating the optimal hedge ratios. The dynamics of Kendall's τ and Pearson's correlation coefficients between 2012 and 2015 are shown in Figure A-5 and Figure A-6, respectively.

All three Kendall's τ were relatively stable during 2012, declined during 2013, sharply rebounded by January of 2015 and then gradually decreased in the second half 2015. The evolution of Pearson's correlation coefficients follows a similar pattern.

Thus, the dynamics of the dependence measures is indeed more consistent with the behavior of the optimal hedge ratios than the dynamics of price levels. In particular, the periods of substantial deviations between vector hedge ratio and single hedge ratio seem to roughly coincide with the periods of decline in the dependence measures. In order to verify this result more formally, we run a regression analysis of calculated optimal hedge ratios on the corresponding dependence measures computed for log returns (Kendall's τ for LPM_2 hedge ratios and Pearson's correlation for MV hedge ratios). The results of the regressions are summarized in Table B-6 for LPM_2 and in Table B-7 for MV. Most of the dependence measures are significant and contribute to explaining the optimal hedge ratios. This evidence supports our conjecture that the behavior of vector hedge ratios in the multi-commodity settings is driven by the cross-dependence between spot and futures log returns of different commodities.

II.6. Conclusions

The objective of this study is to investigate the effectiveness of crack spread hedging strategies during a period of high volatility and changing patterns of dependence in the prices and log returns of crude oil and petroleum products. To that end, a moving window approach was used to calculate the optimal hedge ratios implied by the LPM_2 and minimum variance criteria for each trading day between January 1, 2012, and December 31, 2105. Two cases were considered — hedging all three commodities (crude oil, gasoline, and heating oil) in a fixed 3:2:1 proportion (single hedge ratio) and allowing for separate hedge ratios for each commodity (vector hedge ratio). Hedging effectiveness, expected profit and expected shortfall at 5% were used to measure the hedging performance of the constructed hedging strategies.

The commonly used way of hedging the crack spread at the fixed 3:2:1 proportion is found to be generally less effective in reducing price risk than a strategy allowing for hedging individual commodities separately. This result is robust across several hedging criteria and measures of hedging performance used. Differences in hedge ratios and hedging performance are most pronounced during 2013 and 2015.

The deviations between the single and vector hedge ratios—as well as the corresponding improvements in hedging performance—seem to be unrelated to changes in the levels of spot and futures prices, nor are they related to pairwise correlations between the spot and futures log returns of individual commodities. However, the cross-dependence structure between the futures log returns of different commodities seems to explain the behavior of the optimal hedge ratios fairly well. When the measures of cross-dependence (Kendall's τ and Pearson's correlations) are relatively stable, the differences between the single and vector hedge ratios are relatively small, and so are the improvements in hedging performance. However, during periods of high variability in the cross-dependence structure between prices of different commodities, the strategy of hedging individual commodities separately substantially outperforms that of hedging the crack spread in a fixed proportion.

From a practical standpoint, these results suggest that refineries can generally achieve a better risk-reduction performance by hedging individual commodities than by hedging the crack spread in a fixed 3:2:1 proportion. The advantage of hedging commodities individually becomes particularly important during periods characterized by greater variation of the cross-dependence between the log returns of individual commodities. Finally, using LPM_2 as a hedging criterion may not only help hedgers to better track downside risk, but also appears to lead to higher expected profit and a lower expected shortfall.

CHAPTER III.

PHYSICAL MARKET AND WTI/BRENT PRICE SPREAD

III.1. Introduction

Crude oil is one of the most important industrial commodities. A variety of crude oils of different characteristics are produced and traded around the world. Among them, West Texas Intermediate (WTI), Brent and Dubai Crude are three primary benchmarks. WTI and Brent are both light (low density) and sweet (low sulfur) crude oils, making them ideal for refining petroleum products. Dubai/Oman is a medium sour crude oil with higher density and sulfur content. WTI is produced and primarily used as a benchmark in the U.S. WTI is distributed mainly by the pipeline system, which is considered more flexible, and can be delivered to 'landlocked' areas. The United States has been divided into five Petroleum Administration for Defense Districts (PADD) (see Figure A-7). Cushing, Oklahoma in PADD2, is a key hub with many intersecting pipelines as well as storage facilities. It has served as the price settlement point for WTI on the New York Mercantile Exchange since 1983. The applications of hydraulic fracturing and horizontal drilling technologies have caused a boom in shale oil production over the last few years. According to Energy Information Administration, the average daily production of shale oil is about 3.5 million barrels, three times higher than the daily production in 2010 (EIA 2014). The so-called "shale oil revolution" has increased the availability of U.S. domestic energy availability and reduced its dependence on imported energy. Brent Crude is extracted from the North Sea and encompasses four crude blends, viz. Brent, Forties, Oseberg and Ekofisk (BFOE). Brent is waterborne and can be easily transported to distant locations by oil tankers, it serves as an international crude oil benchmark and is more responsive to global market fundamentals. Norway and United Kingdom are two major oil producers in the North Sea. The Brent and Forties blends are produced offshore in the waters of the UK, and the Ekofisk and Oseberg blends are mainly produced offshore in the waters of Norway (EIA, 2016). The North Sea region is experiencing faster-than-expected decline in production, mainly due to the aging fields and increasing production costs. Brent production fell by 38% between 2010 and 2013, which is approximately 500 million barrels per day of oil production (CME, 2014). Even though the benchmark itself accounts for only a small portion of total world crude production, it remains a key indicator for world crude oil pricing.

The concept of “globalization” in oil market was brought up by Weiner (1991). The basic idea of oil market globalization is that supply and demand shocks to oil prices in one region can transfer into other regions quickly, making prices of crude oils with same quality move closely together. Based on this hypothesis, price spread between crude oils with similar quality should only consists of quality discount, transportation cost, and time discount. WTI and Brent are both light and sweet forms of crude oil, therefore spread between WTI and Brent is supposed to be nearly constant over time (Fattouh, 2010). However, empirical evidence shows that notable variations exist in WTI/Brent spread, particularly after 2010 (see Figure A-8). In this paper, we study the dynamics of WTI/Brent price spread by investigating two questions: (1) is WTI/Brent price spread stationary over time? and (2) what factors are driving the variations in WTI/Brent spread?

The properties of the WTI/Brent price spread as a time series have been studied in the prior literature. Before 2010, most authors find WTI/Brent spread to be a stationary process. Gülen (1997, 1999) finds that oil prices in different markets move closely both in the short run and in the long run. Fattouh (2010) also finds that several pairs of different crude oil price differentials follow stationary processes. After 2011, consistent with Figure A-8, different pattern has been observed. Buyuksahin et al. (2013) show strong evidence to support the hypothesis that there are two breakpoints in the WTI/Brent spread in 2008 and 2010. Chen, Huang and Yi (2015) find that WTI/Brent crude oil price spreads changes from a stationary time series to a non-stationary time series in 2010.

However, the reasons behind the recent variations in WTI/Brent spread have not been studied much. Some factors identified as contributing to the WTI/Brent price spread include inventory in Cushing Oklahoma (Büyüksahin et al., 2013; Li, Mizrach and Otsubo, 2015), macroeconomic conditions or business activity (Büyüksahin et al., 2013), Chinese demand (Li, Mizrach and Otsubo, 2015), Canadian crude imported into PADD2 (Büyüksahin et al., 2013), and financial market liquidity and activity (Büyüksahin et al., 2013; Heidorn, 2015). Even though factors from different perspectives have been considered by researchers, there is no available work focusing on the explanatory power of oil market fundamentals, such as supply, demand, inventory, etc., as a system.

This paper attempts to further this line of inquiry by conducting a comprehensive analysis of factors affecting the dynamics of WTI/Brent spread. In particular, we select physical market variables that can be potential drivers of WTI/Brent spread and estimate a Structural Vector Autoregressive (SVAR) model to explore the response of WTI/Brent spread to structural shocks from the physical market. A procedure suggested by Bai and Perron (1998, 2003) is used to detect the structural break in the WTI/Brent spread series. The SVAR model is then estimated on two sub-samples of data defined by the breakpoint found. The paper is structured as follows. Section 2 studies the dynamics of WTI/Brent price spread and identifies a structural break. Physical market variables and corresponding data information are discussed in Section 3. Section 4 explains the theoretical framework and identification method of Structural Vector Autoregressive model (SVAR) as well as the empirical results. Section 5 provides concluding remarks.

III.2. Historical Dynamics of the WTI-Brent Spread

Our sample period spans from January 1994 to March 2016, with monthly data on WTI and Brent spot prices collected from U.S. Energy Information Administration. The price spread between WTI and Brent is shown in Figure A-8. During 1994-2009, WTI has been traded at a slight premium to Brent crude —$1.52 per barrel (bbl) higher, on average, — probably due to higher quality (sweeter and lighter) of the former. However, from 2010 onward, the prices of WTI and Brent started diverging, with WTI traded at an average discount of around $8.69/bbl relative to Brent.

III.2.1. Structural Change Test

An implicit assumption of any econometric model is that within-sample parameters are constant over time. A structural break test is conducted before the modeling part to avoid possible instability in model parameters. We apply a procedure suggested by Bai and Perron (1998, 2003), which computes the breakpoints in regression relationships based on a dynamic programming approach. The breakpoint is located by the maximum of a sequence of F-statistics (Zeileis et al., 2003). Bai and Perron procedure has advantages over Chow's breakpoint test (Chow, 1960) in that it does not require the pre-specification of the break date. The procedure also allows us to test for the presence of multiple structural changes.

The results suggest a structural break in December 2010 with 95% confidence interval ranging from August 2010 to January 2011. Therefore, two sub-sample periods separated by the breakpoint are considered in the subsequent analysis. The first sample includes 203 observations spanning January 1994 to November 2010. The second sample includes 64 observations from December 2010 to March 2016.

III.2.2 Unit Root Test and Co-integration Test

The augmented Dickey-Fuller test and Philip-Perron test have been applied to WTI and Brent price series in each sub-sample with the null hypothesis of data series being nonstationary. The results of the unit root tests in levels and in first difference are shown in Table B-8. We fail to reject the null hypothesis of non-stationarity for WTI and Brent prices in levels. However there is sufficient evidence to reject non-stationarity for first-differenced series, i.e. WTI and Brent price series are both I(1) processes.

As suggested by Engle and Granger (1987), multiple non-stationary time series may share a common stochastic trend that is stationary. To test if there is such a common stochastic trend underlying the WTI and Brent price processes, we follow the full information likelihood procedure of Johansen (1988) and Johansen and Juselius (1990). In particular, we estimate the Vector Error Correction Model (VECM)

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta Y_{t-1} + \mu_i \tag{11}$$

where $\mathrm{Y} = [\mathrm{WTI}, \mathrm{Brent}]$, Π is a 2×2 matrix which can be decomposed as $\Pi = \alpha\beta'$; α and β are 2×r coefficient matrices measuring the short- and long-run adjustment of the system, respectively. The hypothesis tested are

$$H_0\!: r \leq R \quad \text{and} \quad H_1\!: r \geq R \tag{12}$$

where r is the co-integrating rank, R is an integer number, and $0 \leq r \leq 2$.

The co-integration test results are shown in Table B-9. WTI and Brent have a single co-integrating vector ($r = 1$) in the first sub-sample (prior to December 2010), but they are not co-integrated in the second sub-sample. The change in co-integration property confirms the structural break test result reported in section 2.1.

III.3. Structural Vector Autoregressive Model (SVAR)

III.3.1. Theoretical Framework

Following Killian (2011), we consider a n×1 vector Y_t

$$Y_t = \begin{bmatrix} Y_t^1 \\ \vdots \\ Y_t^n \end{bmatrix} \tag{13}$$

where $\mathrm{t} = 1,2, \dots, \mathrm{T}$.

Assume that Y_t can be modeled using a structural VAR of a finite order p, i.e.

$$B_0 Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + \varepsilon_t \tag{14}$$

where ε_t are serially uncorrelated structural shocks with mean zero, i.e.

$$\mathrm{E}(\varepsilon_t | Y_{t-1}, Y_{t-2}, \dots, Y_{t-P}) = 0 \tag{15}$$

$$\mathrm{E}(\varepsilon_t \varepsilon_t') \equiv \Sigma_\varepsilon = \begin{bmatrix} \sigma_1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_p^2 \end{bmatrix} \tag{16}$$

The SVAR model in a compact form is

$$B(L) Y_t = \varepsilon_t \tag{17}$$

where $B(L) \equiv B_0 - B_1 L - B_2 L^2 - \cdots - B_p L^p$ is the autoregressive lag order polynomial.

For estimation purposes, the SVAR model is converted to its reduced form, VAR model, by pre-multiplying both side by B_0^{-1}

$$B_0^{-1} B_0 Y_t = B_0^{-1} B_1 Y_{t-1} + B_0^{-1} B_2 Y_{t-2} + \cdots + B_0^{-1} B_p Y_{t-p} + B_0^{-1} \varepsilon_t \tag{18}$$

Thus equation (14) can be rewritten in the reduced form as

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t \tag{19}$$

where $A_i = B_0^{-1} B_i, i = 1, 2, \dots, p, u_t = B_0^{-1} \varepsilon_t, t = 1, 2, \dots, T$.

While the structural shocks are serially uncorrelated, the reduced-form residuals are not. Consistent estimates of the reduced-form parameters $A_i,\ i = 1, 2, \dots, p$ and the reduced-form errors u_t can be obtained. However, the reduced-form errors u_t are basically weighted average of structural shocks ε_t, and thus cannot tell us about the response of Y_t to structural shocks. Therefore, the main task would be to identify the transformation matrix B_0^{-1}.

III.3.2. Identification of SVAR Model: Recursiveness Assumption

For a n -dimensional vector Y_t, the transformation matrix B_0^{-1} is a $n \times n$ matrix with $\frac{n \times (n-1)}{2}$ free parameters. Identification can be achieved by imposing restrictions on the elements of B_0. Restrictions on the parameters can take on many forms, such as recursiveness assumption, short-run restrictions, long-run restrictions, sign-restrictions, etc. (Kilian, 2011). In recursively identified models, reduced-form residuals are ordered in the vector ε_t and made uncorrelated, or "orthogonalized", so as to allow separation of structural residuals from the reduced-form residuals. Short/long-run restrictions assume short/long-run response of variables to shocks, and sometimes can be combined in estimating B_0^{-1}. Identifications by sign restrictions are achieved by restricting the sign of the response of variables to structural shocks.

Our model is identified by recursiveness assumption. The recursiveness assumption has been extensively used in literatures on energy market (see, for example, Kilian, 2009) and is justified in our case by the economic rationale. In this paper, we study physical market variables including supply, demand and inventory factors. Since frequent changes to either production or import plan is costly, supply does not respond contemporaneously to demand shocks, while demand can respond to supply shocks right away (Stevens, 2014). Inventory level changes reflect both supply and demand shocks. Based on this consideration, supply or production shocks are put before demand shocks and inventory shocks are placed after demand shocks in the vector of structural shocks ε_t.

Under recursiveness assumption, the reduced-form residuals are then orthogonalized by using Cholesky decomposition (Kilian, 2011), so that B_0^{-1} becomes a low triangular matrix. Thus $u_t = B_0^{-1}\varepsilon_t$ is written as

$$\begin{bmatrix} u_t^1 \\ \vdots \\ u_t^n \end{bmatrix} = \begin{bmatrix} b_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ b_{n1} & \cdots & b_{nn} \end{bmatrix} \begin{bmatrix} \varepsilon_t^1 \\ \vdots \\ \varepsilon_t^n \end{bmatrix} \tag{20}$$

III.3.3. Selection of Variables

Previous literature suggests that supply, demand, and inventory are physical market factors explaining the behavior WTI/Brent spread.

Supply of crude oil is mainly determined by its production. We use the U.S. Field Production of Crude Oil — an indicator reported by EIA — to represent the WTI supply and Norway production as a proxy for Brent supply. Demand for crude oil is primarily driven by business activity. Purchasing Managers' Index (PMI) is an indicator of the economic health of manufacturing sector. The data for the index are derived from monthly surveys of companies in seven manufacturing sectors in the U.S. Given that a large part of crude oil is consumed by the manufacturing sector, the PMI is used as an indicator for WTI demand.

Crude oil inventory is often created by geographical differences between the production and refining locations. Brent crude is carried by oil tankers, thus there is no aggregate inventory. WTI crude is mainly transferred by pipelines, with constraints on the pipeline capacity creating surplus or shortage in different areas and thus affecting the price. The key WTI storage facilities are located in Cushing, Oklahoma, in PADD2, which is also the delivery point for WTI. Therefore, we use PADD2 inventory to represent the WTI inventory.

Given the selection of variables, we consider a 5×1 vector Y_t that includes WTI supply, Norway production (proxy for Brent supply), PMI (proxy for U.S. domestic demand), PADD 2 inventory, and WTI/Brent Spread (in real dollars).

Based on the recursiveness assumption, supply or production shocks are put before demand shocks in the vector of structural shocks ε_t. More specifically, because Norway production is relatively small and mainly affected by its own producing cost, the corresponding variable is placed in the model before the U.S. production. Storage shock is placed after the demand shocks for the reason that supply and demand changes can be immediately reflected in storage. In addition, because oil prices respond to supply shocks, demand shocks and storage shocks contemporaneously, WTI/Brent spread shock is placed the last in the vector ε_t.

$$Y_t = \begin{bmatrix} Y_t^{\_production} \\ Y_t^{U.S.\_production} \\ Y_t^{PMI} \\ Y_t^{PADD2\_Inventory} \\ Y_t^{spread} \end{bmatrix} \tag{21}$$

III.4. Data and Empirical Results

III.4.1. Data

Monthly data from January 1994 to March 2016 (267 observations) are used to perform the analysis outlined in the previous section. The SVAR model includes five variables, viz. U.S. Production, Norway Production, PMI, PADD 2 inventory and WTI/Brent price spread. Monthly WTI and Brent prices, U.S. production, Norway production and PADD2 inventory data are sourced from US Energy Information Administration. PMI data is obtained from Datastream. Corresponding time series plots are shown in Figure A-8 through Figure A-12. Norway production (Figure A-9) shows a steep decline beginning with early 2000s due to the quickly rising production cost. In contrast, the U.S. crude oil production experiences a boom in recent decade (Figure A-10) due to development of shale oil fracking technology. The Purchasing Manager Index (PMI) moves with the business cycle and shows a lot of ups and downs (Figure A-11), with the deepest trough observed during the 2008-2009 financial crisis. The trend in PADD2 inventory (Figure A-12) follows the trend in U.S. production. Table B-10 presents the descriptive statistics of all five variables for both the full-sample and two sub-samples.

III.4.2. Empirical Results

Given that a structural break presents in WTI/Brent price spread series, two separate SVAR models are specified and estimated over the two sub-samples[9].

The optimal lags are selected using the Schwarz criterion. Both sub-sample periods have optimal lag order equal to one. With lag orders specified, estimations of SVAR models produce impulse response functions. The latter describe the response of a variable to a one-time only shock from another variable, keeping all other variables constant. In this paper, we focus on examining the response of WTI/Brent price spread to shocks in Norway Production, U.S. Production, PMI and PADD 2 inventory. Figure A-13 through Figure A-16 shown the estimated impulse responses with the corresponding 95% standard error bands.

WTI/Brent price spread shows insignificant response to a one-time only shock in Norway production in both sub-sample periods (Figure A-13 and Figure A-14). U.S. production shock, however, has a significantly negative impact on WTI/Brent price spread in the first sub-sample period (Figure A-15), i.e., an unexpected increase in U.S. production would cause WTI price to decrease relative to Brent. The effect starts right after the shock and lasts for about one month. The direction of response is reversed in the second sub-sample period (Figure A-16), in which the impact of U.S. production shock becomes significantly positive starting from the second month. Generally, Figure A-13 through Figure A-16 suggest that the WTI/Brent price spread is driven primarily

[9] The second sub-sample contains 64 observations, so a small-sample degrees-of-freedom adjustment is used when the model is estimated in STATA.

by the variations in the U.S. production and is rather insensitive to Norway production. This can be a consequence of small and declining amount of Norway production relative to U.S. production.

WTI/Brent price spread also shows a significant response to shocks in PMI in sub-sample 1 with a 2-month delay (Figure A-17). In other words, an unexpected grow in business activity in U.S. will cause a slight increase in WTI price relative to Brent. During sub-sample 2, WTI/Brent price spread doesn't show significant response to unexpected shocks in PMI (Figure A-18).

Finally, WTI/Brent price spread reacts significantly and immediately to shocks in PADD2 inventory for both sample periods (Figure A-19 and Figure A-20). A positive shock in PADD2 inventory has a negative impact on relative price of WTI. The effect lasts for more than ten months in sub-sample 1 but fades away in just one month in sub-sample 2.

III.5. Conclusion

This paper analyzes the time series dynamics of WTI/Brent spread and how it responds to different physical market shocks, including supply shocks, demand shocks and inventory shocks. Bai-Perron test procedure (1998, 2003) indicates a structural break in December 2010, with the 95% confidence interval ranging from Aug 2010 to January 2011. Based on this result, the sample of data is split into two sub-sample periods separated by the structural break, one spanning January 1994 to November 2010 and the other lasting from December 2010 to March 2016. Structural Vector Autoregressive

(SVAR) models are estimated for each sub-sample period and impulse response functions are generated.

Even though the generally patterns are similar, impulse response functions generated from SVAR model show different behaviors in two sub-sample periods. During the first sub-sample, WTI/Brent price spread is very sensitive to production shocks, both in Norway and in U.S. Despite some delays, it also responds positively to grows in business activity agented by PMI index. WTI/Brent price spread reacts significantly right after shocks in PADD2 inventory and the effect will last for a long time. During the second sub-sample, some of the reactions are less significant (to PMI) or last for a shorter time period (to PADD2 Inventory). Distortions are also observed (to U.S. production), probably due to the small sample size of sub-period 2.

To sum up, despite similarities in directions of response, the responding time as well effect size to physical market shocks are different for WTI/Brent price spread before and after the structural break. Thus it’s important to separate the whole sample period into different sub-samples when dramatic changes in WTI/Brent price spread are observed. Furthermore, closely monitoring the supply/production and demand/business activity in U.S. is more important in understanding WTI/Brent price spread. WTI/Brent responds more quickly to supply/production shocks than the demand/business activity shocks.

CHAPTER IV.

CORRELATION AND VOLATILITY SPILLOVER BETWEEN CRUDE OIL AND STOCK MARKET RETURNS: A SECTOR LEVEL ANALYSIS

IV.1. Introduction

Traditionally, commodity derivative market has been assumed to have very low correlation with the conventional capital market, thus providing an alternative investment for portfolio diversification, hedging etc. (e.g. Silvennoinen and Thorp, 2013; Kang et al., 2016). There is evidence showing that a portfolio consisting of both commodities and stocks can have higher return and lower risk than a portfolio only containing stocks (Gorton and Rouwenhorst, 2006). Therefore, the literature generally suggests adding commodity to a portfolio as a very effective way to increase portfolio return while reducing potential risk.

Since early 2000s, commodity derivative markets have attracted growing interests from investors. The U.S. Commodity Futures Trading Commission (CFTC) reported in 2008 that the total value of commodity-related investment by institutional investors increased from about $15 billion in 2003 to more than $200 billion in 2008 (Tang and Xiong, 2012; Cheng and Xiong, 2014). This process of large capital inflows into commodity market is sometimes referred as “commodity financialization”. As a side effect, the linkage between commodity and equity market has been substantially impacted. In particular, increasing commodity-equity correlation and volatility transmission has been observed in recent decade, especially after the financial crisis of

2008-2009 (e.g. Creti et al. (2013); Büyüksahin and Robe (2014)). This development challenges the conventional assumption underlying portfolio diversification and commodity hedging strategies and motivates the research objective of our paper, which is to analyze the dynamics of correlation structure and volatility transmission mechanism between commodity and equity markets.

In particular, we focus on correlations and volatility spillovers between returns on crude oil futures and stock market sectors. Crude oil is the most actively trading and volatile commodity and has significant impact on economic activity. Arouri and Nguyen (2010) find the sensitivities of different stock market sectors to oil price fluctuations are not necessarily uniform, which justifies studying the impacts of oil price volatility at sector level instead of the aggregate market level. Sector-level analysis can keep the industry-specific characteristics of stocks and also provides insights for portfolio management since some sectors might turn out to be better channel for investment diversification. We use the Standard and Poor's Depository Receipts (SPDRs) to represent different stock market sectors. Sector SPDRs are Exchange Traded Funds (ETF) that keep track of the price and yield performance of the stocks in underlying sectors and are actively traded throughout the day on NYSE Arca. DCC-GARCH model of Engle (2002) is used to estimate dynamic correlation between the returns of crude oil futures, S&P 500 index futures and six Sector SPDRs. Volatility connectedness measurement of Diebold and Yilmaz (2012, 2014, 2015) is adopted to measure the volatility spillovers.

The paper is organized as follows. Section 2 provides a review of relevant literature. Section 3 presents the modeling framework for estimating dynamic correlations and volatility spillover. Data and preliminary analysis are summarized in Section 4. Empirical results are discussed in Section 5. Section 6 provides concluding remarks.

IV.2. Literature Review

Since 2000s, there has been growing literature focusing on the interaction between commodity and equity markets. Most of the empirical studies find that the correlation and volatility transmission between the two markets changed significantly particularly after 2007-2009. Creti et al. (2013) investigate twenty-five different commodities covering energy, precious metals, agriculturals, non-ferrous metals, livestock, etc., and show that the correlations between commodity and stock returns are highly volatile over the period between January 2001 and November 2011, with the 2007-2008 financial crisis playing a key role in enhancing the link between the commodity and stock markets. Büyüksahin and Robe (2014) analyze CFTC non-public dataset of trader positions and find that the commodity–equity correlations soared after the financial crisis in the fall of 2008 and remained at a high level since then. They suggest hedge funds could be a transmission channel given their increasing positions in the commodity futures market.

Crude oil is the most important industrial commodity and has shown to be closely linked to the stock market. Stock values are affected by economic condition and crude oil has a direct and significant impact on the economy. For example, Sadorsky

(1999) provides empirical evidence for oil price volatility affecting economic activity and playing an important role in explaining stock market movement.

However, most of the articles studying crude oil-stock market relationships focus on broad-based national or reginal market indices and very few studies have looked into the impact of oil price change on individual sectors in stock market. The majority of existing studies investigate only one or two specific stock market sectors. Sadorsky (2001) shows that an increase in oil price can lead to higher returns in oil and gas companies' stocks in Canadian stock market. Nandha and Brooks (2009) examine the link between oil prices and stock returns in transport sector in 38 countries across the world. Their findings suggest oil prices have greater impact on transport sector in developed countries. Arouri et al. (2011) find significant volatility interaction between oil and stock market sectors in both Europe and the U.S. across different industry sectors. In particular, they show that in Europe, transmission of volatility is more apparent from the crude oil market to the stock market, while in the U.S., the interaction is more bidirectional. The shock transmission is more significant in financial, utility, and technology sectors and less pronounced in automobile & parts sector. Kilian and Park (2009) further point out that the response of stock sector returns to oil market largely depends on whether the oil price change is driven by the shocks in demand or supply side.

Analysis of dynamic correlations requires one to model the co-movement of returns of multiple assets. Different types of multivariate generalized autoregressive heteroskedasticity (MGARCH) models have been used in the literature for this purpose, including bivariate GARCH (Ji and Fan, 2012), VAR-BEKK-GARCH and VAR-DCC-GARCH (Mensi et al., 2014), CCC-AGARCH, VARMA-AGARCH (Sadorsky, 2014), etc.

MGARCH models can also be used to model volatility spillover, however, they can only produce the variance-covariance matrix with no information on the direction of spillovers (Awartani and Maghyereh, 2013; Antonakakis and Kizys, 2015; Kang et al., 2016). Nazlioglu et al. (2013) use causality-in-variance test of Hafner and Herwartz (2006) to detect the existence of volatility spillovers between the crude oil and agricultural commodity returns. Badshah (2013) and Nazlioglu et al. (2013) use impulse response functions derived from Structural Vector Autoregressive (SVAR) model to examine how other variables respond to a one-time only shock in one variable. Even though an SVAR model with impulse response function can show the time and size of the reaction, it requires additional assumptions on the ordering of variables. Diebold and Yilmaz (2012, 2014, 2015) introduce a new method to measure volatility spillover based on forecast error decomposition derived from generalized vector autoregression (VAR) model, which is invariant to the ordering of the variables and enables the calculation of both the direction and the magnitude of volatility spillover.

In this paper, we extend the existing literature in several ways. First, we study the oil-equity market linkage both for the aggregate market as well as sector by sector. Furthermore, we analyze both correlation and volatility transmission between oil and stock market. We use the DCC-GARCH model of Engle (2002) to estimate the return co-movement between crude oil futures, S&P500 index futures, and stock market sector indicators. The volatility connectedness framework (Diebold and Yilmaz, 2012, 2014 & 2015) derived from a generalized VAR framework is adopted to measure volatility spillover. A rolling window analysis is used to show the evolution of volatility spillover over time.

IV.3. Modeling Framework

IV.3.1. DCC-GARCH Framework

We use dynamic conditional correlation GARCH (DCC-GARCH) model introduced by Engle (2002) to model the time evolution of correlations between crude oil and stock market sector returns based on futures prices of crude oil and S&P500 index and prices of sector ETFs traded on NYSE Arca. Daily returns are calculated by taking the difference between the logarithms of two consecutive prices $r_t^i = ln(p_t^i) - ln(p_{t-1}^i)$, where r_t^i is the log return of variable i at period t, p_t^i is the price level of variable i at time t. We denote r_t the vector of returns for crude oil, S&P500 index, and six stock sectors, viz. $r_t = (r_t^{Crude}, r_t^{SP500}, r_t^{XLY}, r_t^{XLP}, r_t^{XLE}, r_t^{XLF}, r_t^{XLB}, r_t^{Crude})$. DCC-GARCH model can be written as:

$$r_t = \mu_t + \varepsilon_t \tag{22}$$

$$\varepsilon_t = H_t^{1/2} z_t \tag{23}$$

$$H_t = D_t R_t D_t \tag{24}$$

where r_t is an 8×1 vector of log returns of 8 variables at time t, μ_t is an 8×1 vector of the expected values of the conditional r_t, ε_t is an 8×1 vector of the residuals with $\mathrm{E}(\varepsilon_t) = 0$ and $\mathrm{Var}(\varepsilon_t) = H_t$, H_t is an 8×8 matrix of conditional variances of ε_t at time t

and $H_t^{1/2}$ can be obtained by a Cholesky factorization. D_t is an 8×8 diagnonal matrix of conditional standard deviations at time t, i.e. $D_t = diag\{\sqrt{h_{i,t}}\}$, R_t is an 8×8 symmetric matrix of conditional correlations at time t, and z_t is an 8×1 vector of i.i.d. error terms with $\mathrm{E}(z_t) = 0$ and $\mathrm{Var}(z_t) = I$.

The diagonal elements $h_{i,t}$ in D_t, evolve according to a univariate GARCH process of the form

$$h_{i,t} = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1} \tag{25}$$

The elements of H_t are $H_t = \sqrt{h_{i,t}h_{j,t}}\rho_{i,j}$. Since R_t is positive definite matrix, it can be decomposed as $R_t = Q_t^{*-1}Q_tQ_t^{*-1}$, where Q_t is a positive definite matrix containing the conditional variances of ε_t and Q_t^{*-1} is the inverted diagonal matrix with the square roots of the diagonal elements of Q_t, viz.

$$Q_t^{*-1} = \begin{bmatrix} 1/\sqrt{q_{Crude\_Crude}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\sqrt{q_{XLK\_XLK}} \end{bmatrix} \tag{26}$$

The DCC (1,1) -GARCH model is then given by

$$Q_t = (1 - a - b)\bar{Q} + \mathrm{a}\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{27}$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardized errors ε_t, $\bar{Q} = E(\varepsilon_t\varepsilon_t')$. The dynamic conditional correlations are then given by

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{28}$$

Following Engle (2002), the model is estimated using a two-step maximum likelihood method. The likelihood function is given by

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + ln|H_t| + r_t' H_t^{-1} r_t) = -\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + 2ln|D_t| + ln|R_t| + \varepsilon_t R_t^{-1} \varepsilon_t') \tag{29}$$

GARCH parameters are estimated in the first step and the conditional correlations are estimated in the second step.

IV.3.2. Measuring Volatility Spillover

We follow Diebold and Yilmaz (2015), who in turn use the approach proposed by Garman and Klass (1980), to construct an estimate of a daily range-based volatility as

$$\tilde{\sigma}^2 = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2 \tag{30}$$

where h is the log daily high price, l is the log daily low price, o is the log daily opening price and c is the log daily closing price.

We then estimate a vector-autoregressive (VAR) approximating model and construct the variance decomposition matrix to measure the directional and net volatility connectedness (spillovers) between crude oil and stock market sectors. We assume an n-dimensional VAR(p) model, viz.

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_t \tag{31}$$

where y_t is an $n \times 1$ vector of endogeneous variables, Φ_i are $n \times n$ autoregressive coefficient matrices and ε_t is a vector of i.i.d. error terms with $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is written as

$$y_t = \sum_{j=1}^{\infty} \mathrm{A}_j \varepsilon_t \tag{32}$$

where A_j is an $n \times n$ coefficient matrix that follows a recursion of the form $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \cdots + \Phi_p A_{j-p}$ with A_0 being the $n \times n$ identity matrix and $A_j = 0$ for $\mathrm{j} < 0$. The moving-average coefficients are transformed to obtain variance decompositions, which allow us to split the H-step-ahead forecast error variances of each variable into parts that are attributable to the system shock in the VAR (p) model.

The calculation of variance decomposition often requires orthogonalization of VAR shocks, which can be achieved by Cholesky factorization or the structural VAR identification. In these cases, however, the variance decompositions depend on the ordering of variables (for Cholesky factorization) or the identification assumptions (for structural VAR). To avoid this problem, we use the generalized approach of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) that allows contemporaneously correlated VAR innovations. Following the KPPS method, variable j's contribution to variable i's H-step-ahead generalized forecast error variance is

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)} \tag{33}$$

where σ_{jj} is the standard deviation of ε_j, and e_i is the selection vector with one as the i^{th} element and zeros otherwise. Note that the row sums of the variance decomposition table $\sum_{j=1}^{N} \theta_{jj}^{g..}$ are not necessarily equal to 1. Therefore, each entry of the matrix is normalized by the i^{th} row sum as

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{n} \theta_{ij}(H)} \tag{34}$$

so that, by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

The variable $C_{i \leftarrow j}(H) = \tilde{\theta}_{ij}(H)$ provides a measure of pairwise directional connectedness from j to i at horizon H. The net pairwise directional connectedness can be then calculated as $C_{ij}(H) = C_{i \leftarrow j}(H) - C_{j \leftarrow i}(H)$.

The normalized elements of the generalized variance decomposition matrix can be also used to calculate the directional spillover index, which measures the directional volatility spillovers (DS) received by market i from all other market j ("from") or the directional volatility spillovers transmitted by market i to all other markets j ("to"). The "from" and "to" directional spillover indices are defined as

$$C_{i \leftarrow \cdot}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{35}$$

And

$$C_{\cdot\leftarrow i}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100 \tag{36}$$

The net total directional connectedness for variable i can be calculated by taking the difference between the "to" and "from" measures, i.e.

$$C_i(H) = C_{\cdot\leftarrow i}(H) - C_{i\leftarrow\cdot}(H) \tag{37}$$

We can also aggregate all "from" measures or all "to" measures to calculate the total spillover index (TS), which measures the contribution of volatility spillovers across all variables to the total forecast error variance.

$$C(H) = \frac{\sum_{i=1}^{N} C_{\cdot\leftarrow i}(H)}{N} = \frac{\sum_{i=1}^{N} C_{i\leftarrow\cdot}(H)}{N} \tag{38}$$

IV.4. Data Description

We use daily data of crude oil futures, S&P 500 index futures and six sector SPDRs for the period between January 4, 1999, and December 30, 2016. Continuous series of NYMEX light crude oil futures prices and CME S&P 500 index futures prices are obtained from Datastream. Data for six sector SPDRs, viz. Consumer Discretionary (XLY), Consumer Staples (XLP), Energy (XLE), Financials (XLF), Materials (XLB), and Technology (XLK) are obtained from Yahoo Finance website[10]. The Health Care (XLV), Industrials (XLI), Real Estate (XLRE) and Utilities (XLU) sector SPDRs are not included due to the shortness of data series.

[10] https://finance.yahoo.com/quote/SPY?p=SPY

Table B-11 reports the descriptive statistics of the daily return series for crude oil futures, S&P500 index futures and six sector SPDRs prices. Crude oil futures have the highest average daily return (0.0312) while those for the Financial Sector SPDR are the lowest. Crude oil returns also show the highest volatility followed by the Financial sector SPDR. The Consumer Staple sector prices are the most stable during the sample period. Most of the variables are skewed to the left except for the Financial and Technology SPDRs, which are skewed to the right. Positive skewness in Financials and Technology SPDRs indicate that it is more likely to observe positive returns for these sector than negative returns. The kurtosis value for all return series are above three, indicating a higher peak and fatter tail relative to normal distribution. This is particularly pronounced for the Financial SPDR, which has a kurtosis of 24.9099. The extremely high kurtosis value together with a negative mean and a positive skewness value imply the presence of frequent small losses and less frequent but extreme large gains in the Financial SPDR. The ARCH test (Engle, 1982) rejects the null hypothesis of no ARCH effects, therefore GARCH-based approach is appropriate for modeling the return series.

Results of the unit-root tests are shown in Table B-12. Three different tests (ADF, PP, and KPSS) are consistent in the conclusion of stationary at 1% significance level for all return series.

IV.5. Empirical Result

IV.5.1. Dynamic Conditional Correlation

Twenty-eight pairs of conditional correlations are shown in Figure A-21, Figure A-22, Figure A-23 and Figure A-24. Corresponding summary statistics are presented in

Table B-13, Table B-14, Table B-15 and Table B-16. The static unconditional correlation coefficients, Pearson's correlation coefficient and Kendall's τ, are also reported for comparison purpose.

Generally, the return correlations between crude oil and S&P500 as well as between crude oil and sector SPDRs incresed sharply and peaked during the financial crisis in 2008-2009. Decrease in correlations has been observed around 2014, but they slowly recovered in 2016. Crude oil has the highest correlation with the Energy sector (XLE), followed by Materials sector (XLB). SP500 Index return displays high correlation with all sector SPDRs, which means general stock market conditions play an important role in sub-sectors' returns.

IV.5.2. Volatility Spillover

IV.5.2.1. Static Analysis of Volatility Connectedness

For the pursposes of analysis, we estimate a VAR(5) model with 12-day-ahead forecast error decomposition. The VAR order is selected based on Schwarz Information Criterion. Full sample from January 1999 to December 2016 is used to calculate the static volatility connectedness as shown in Table B-17.

Here cell ij represents variable i's contribution to the forecast error variance due to the shocks in variable j. The diagonal elements measure own volatility spillover and the off-diagonal elements measures the volatility spillover from other variabes. The "From" columns are calculated as row sums exluding diagonal element. These give the total directional connectedness from all others to variable i. The "To" rows are calculated as column sums excluding diagonal element and give the total directional connectedness from variable j to all others. The "Net" row is calculated as the difference between the "to" and "from" total directional connectedness. Here positive values indicate that the corresponding variable is a net transmitter of spillovers while negative values inicate that the corresponding variable is a net receiver.

The net volatility spillover index confirms that the volatility spillover effects are not homogeneous across all variables. Based on the full-sample, crude oil along with Consumer Discretionary (XLY) and Consumer Staples (XLP) sectors are the net receivers while the other sectors together with SP500 are net transmitters. Consumer Discretionary (XLY) sector is the largest receiver and Financials (XLF) is the largest transmitter.

IV.5.2.2. Dynamic Analysis of Volatility Connectedness

Analysis of correlations in Section IV.5.1 indicates that the interaction between crude oil and equity market changes over time and therefore static spillover analysis might ignore time-related information. Therefore, we use a 252-day rolling window of return data to analyze the dynamics of volatility connectedness using the same VAR(5) model with 12-day-ahead forecast error decomposition.

Figure A-25, Figure A-26, Figure A-27, Figure A-28, Figure A-29, Figure A-30, Figure A-31 and Figure A-32 present evolution of net volatility spillover over time for all eight variables. The graphs confirm our conjecture that both the direction and the magnitude of spillovers vary over time. With the exception of Consumer Discretionary

(XLY) sector, which is a receiver during the entire period analyzed, all variables could be both “giving” and “receiving” volatility at different points in time. Crude oil is a net volatility transmitter 60% of the time, and net receiver during the rest of the analyzed period. The transmission periods are 2004 to 2006, 2010 to 2011 and around 2014, when the oil prices were at high levels. When oil prices experience decrease, the net volatility connectedness tends to be negative. Even though S&P500 index is “giving” volatility 70% of the time, it became a net receiver during the 2008-2009 financial crisis. Consumer Discretionary (XLY), which includes industries such as automobiles and components, consumer durables, hotels, restaurants and retailing, etc., is the only consistent net receiver at all times during the sample period. Consumer Staples (XLP) sector covers companies that are primarily involved in developing and producing of consumer products. It serves as a volatility transmitter for less than 10% of the time. Energy (XLE) sector was a net transmitter for most of the time during 2005 and 2015 when the oil prices were high. However, it became a net receiver during 2015 during the collapse of oil prices. As oil prices started recovering from their lowest point in early 2016, the net volatility connectedness of Energy sector also increased. Financials (XLF) sector tracks the stocks of financial service firms. It is a strong net transmitter for over 90% of the time with peaks observed during the 2008-2009 financial crisis and during 2015. Materials (XLB) sector was a net transmitter of volatility 71% of the time, with its role of volatility “giver” most pronounced between 2005 and 2015. Finally, the Technology (XLK) sector tracks stocks performance in high-tech companies such as

Microsoft Corp., AT&T, Cisco, etc. This sector was a net volatility transmitter for 78% of the time and shows a spike in volatility giving during 2000-2002 and around 2016.

IV.5. Conclusions

The goal of this paper is to study the dependence structure and volatility spillover effects between crude oil and stock market between January 1999 and December 2016, both at aggregate market and individual sector levels. Daily data of crude oil futures, S&P 500 index futures and six sector SPDRs ETFs, viz. Consumer Discretionary (XLY), Consumer Staples (XLP), Energy (XLE), Financials (XLF), Materials (XLB), Technology (XLK), are used. DCC-GARCH model of Engle (2002) is adopted to model the dynamic conditional correlation. The volatility connectedness model of Diebold and Yilmaz (2012) is used to model the volatility spillover based on the full sample as well as in a 252-day rolling window.

The results indicate that the dynamic conditional correlation between pairs of variables increased sharply during the 2008-2009 financial crisis. Furthermore, despite some variability, the correlations during the post-crisis period generally remain at a higher level relative to the pre-crisis period. Static analysis of volatility transmission shows that the Financials sector (XLF) is the largest transmitter, followed by Technology sector (XLK), while the Consumer Discretionary (XLY) and Consumer Staples (XLP) sectors are the two largest receivers of volatility spillover. Rolling-window analysis provides a more dynamic perspective on the volatility spillover. Seven out of the eight variables were both “giving” and “receiving” volatility at some point during the sample period. Consistent with the findings of static analysis, Financials

(XLF) and Technology (XLK) sectors are the two strongest volatility transmitters. The roles of crude oil and S&P500 index as transmitters or receivers is highly dependent on the conditions of the market. Crude oil's volatility transmission impact is larger when its price is higher. S&P500 is more likely to be "receiving" volatility when the stock market is in crisis.

Understanding the dependence structure and direction of volatility transmission between crude oil market and sector level stock market are crucial for portfolio design and development of risk management/hedging strategies. The increasing correlation between crude oil and stock market may reduce their substitutability in the portfolio. Analysis of the spillover dynamics provides further insight into building performance of risk management models and hedging strategies under different market conditions.

CHAPTER V.

CONCLUSIONS

Because of oil's dominant role as an energy source, crude oil and its refined product markets are the most important commodity markets for industrialized economies. In recent years, major changes have been observed in the behavior of global oil markets. The highly volatile oil prices and oil-equity relations expose oil market participants as well as portfolio managers to higher levels of risk and call for new risk management strategies. The dissertation addresses different aspects of risk management in multi-commodity setting with application to energy markets.

Chapter II analyzes effectiveness of traditional and alternative hedging strategies during the period of volatile oil price. Optimal strategies are constructed for oil refineries for both 3:2:1 fixed ratio (traditional crack spread) hedging and arbitrary proportion hedging during the periods of relatively stable and volatile oil prices observed in recent years. Minimization of downside risk (LPM_2) and variance are used as alternative hedging objectives. The joint distribution of spot and futures price log returns is modeled using a kernel copula method. The hedging performance of the constructed strategies is compared using hedging effectiveness, expected profit, and expected shortfall. Results suggest that refineries can generally achieve a better risk-reduction performance by hedging individual commodities than by hedging the crack spread in a fixed 3:2:1 proportion. The advantage of hedging commodities individually becomes particularly important during periods characterized by greater variation of the cross-dependence between the log returns of individual commodities. Finally, using LPM_2 as a hedging criterion may not only help hedgers to better track downside risk, but also appears to lead to higher expected profit and a lower expected shortfall.

Chapter III studies the dynamics of WTI/Brent price spread during the period between January 1994 and March 2016 and investigates how the spread responds to different types of physical market shocks. A test for structural breaks in the WTI/Brent price spread indicates a change from a stationary to a non-stationary time series in December 2010. The impact of physical market fundamentals on the dynamics of WTI/Brent price spread is then analyzed using a Structural Vector Autoregressive Model (SVAR) which reflects the response of WTI/Brent price spread to shocks in Norway Crude Oil Production, U.S. Crude Oil Production, PMI economic activity index, and Crude Oil Inventory in U.S. PADD2 . The SVAR model is estimated for each sub-sample period separated by the structural break. Results show that, despite similarities in directions of response, the responding time as well effect size to physical market shocks are different for WTI/Brent price spread before and after the structural break. Thus it's important to separate the whole sample period into different sub-samples when dramatic changes in WTI/Brent price spread are observed. Furthermore, closely monitoring the supply/production and demand/business activity in U.S. is more important in understanding WTI/Brent price spread. WTI/Brent responds more quickly to supply/production shocks than the demand/business activity shocks.

Chapter IV analyzes the dynamics of correlation structure and volatility transmission mechanism between crude oil futures and stock market at both aggregate and individual sector levels. The results indicate that the dynamic conditional correlation between pairs of variables increased sharply during the 2008-2009 financial crisis. Furthermore, despite some variability, the correlations during the post-crisis period generally remain at a higher level relative to the pre-crisis period. Static analysis of volatility transmission shows that the Financials sector (XLF) is the largest transmitter, followed by Technology sector (XLK), while the Consumer Discretionary (XLY) and Consumer Staples (XLP) sectors are the two largest receivers of volatility spillover. Rolling-window analysis provides a more dynamic perspective on the volatility spillover. Seven out of the eight variables were both “giving” and “receiving” volatility at some point during the sample period. Consistent with the findings of static analysis, Financials (XLF) and Technology (XLK) sectors are the two strongest volatility transmitters. The roles of crude oil and S&P500 index as transmitters or receivers is highly dependent on the conditions of the market. Crude oil’s volatility transmission impact is larger when its price is higher. S&P500 is more likely to be “receiving” volatility when the stock market is in crisis.

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APPENDIX A.

FIGURES

Figure A-1: Spot prices of crude oil (CL), regular gasoline(RB) and heating oil (HO) between 01/01/2012 and 12/31/2015.

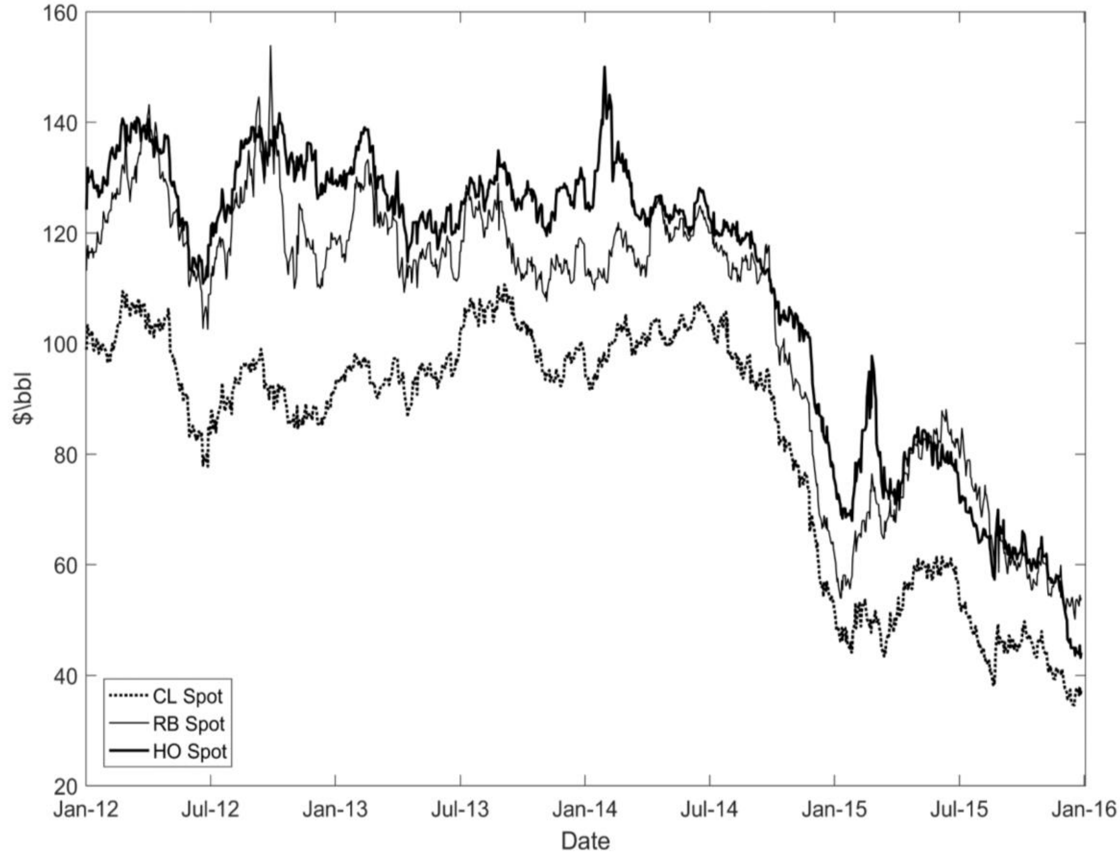


Figure A-2: Futures prices of crude oil (CL), regular gasoline (RB), and heating oil (HO) between 01/01/2012 and 12/31/2015 (continuous series).

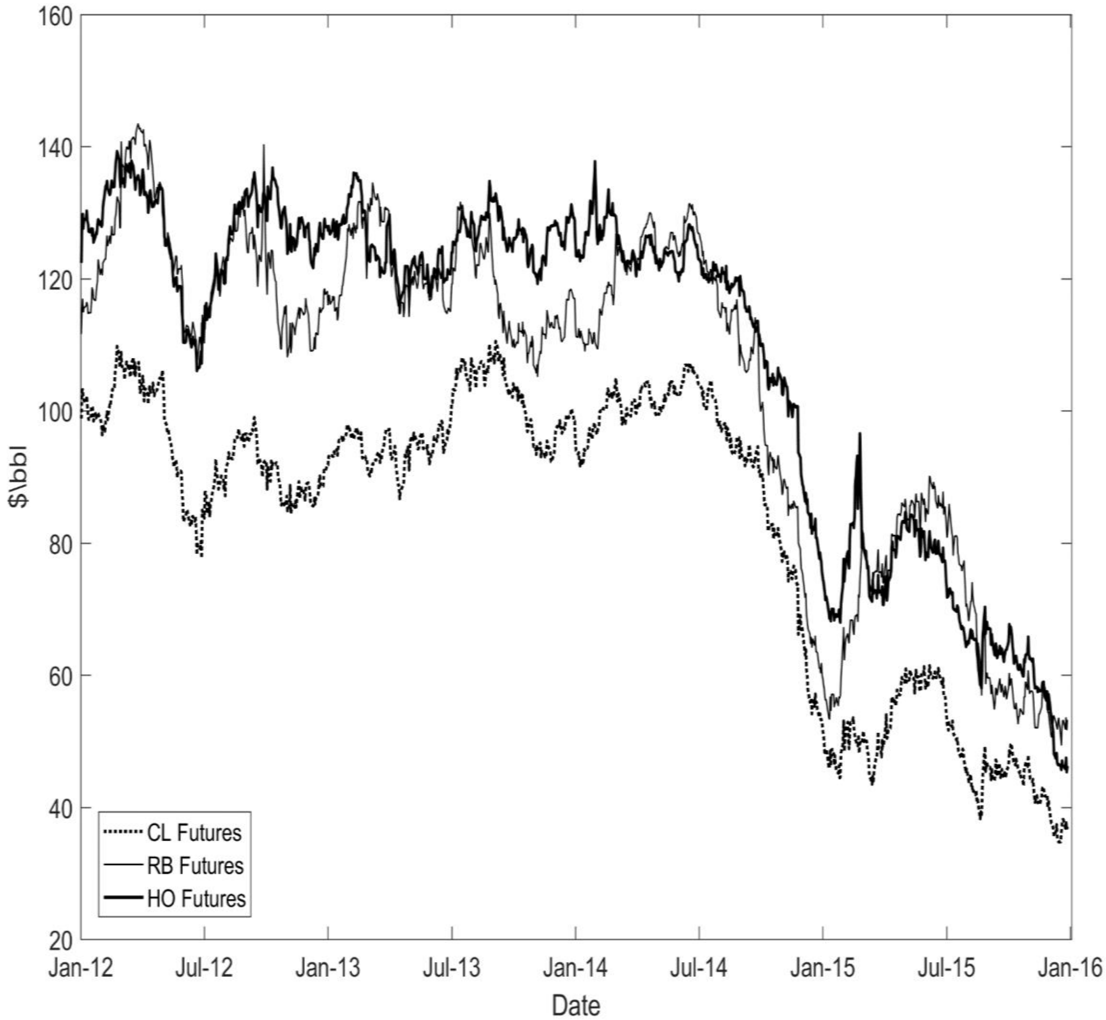


Figure A-3: Optimal hedge ratios under the LPM_2 criterion

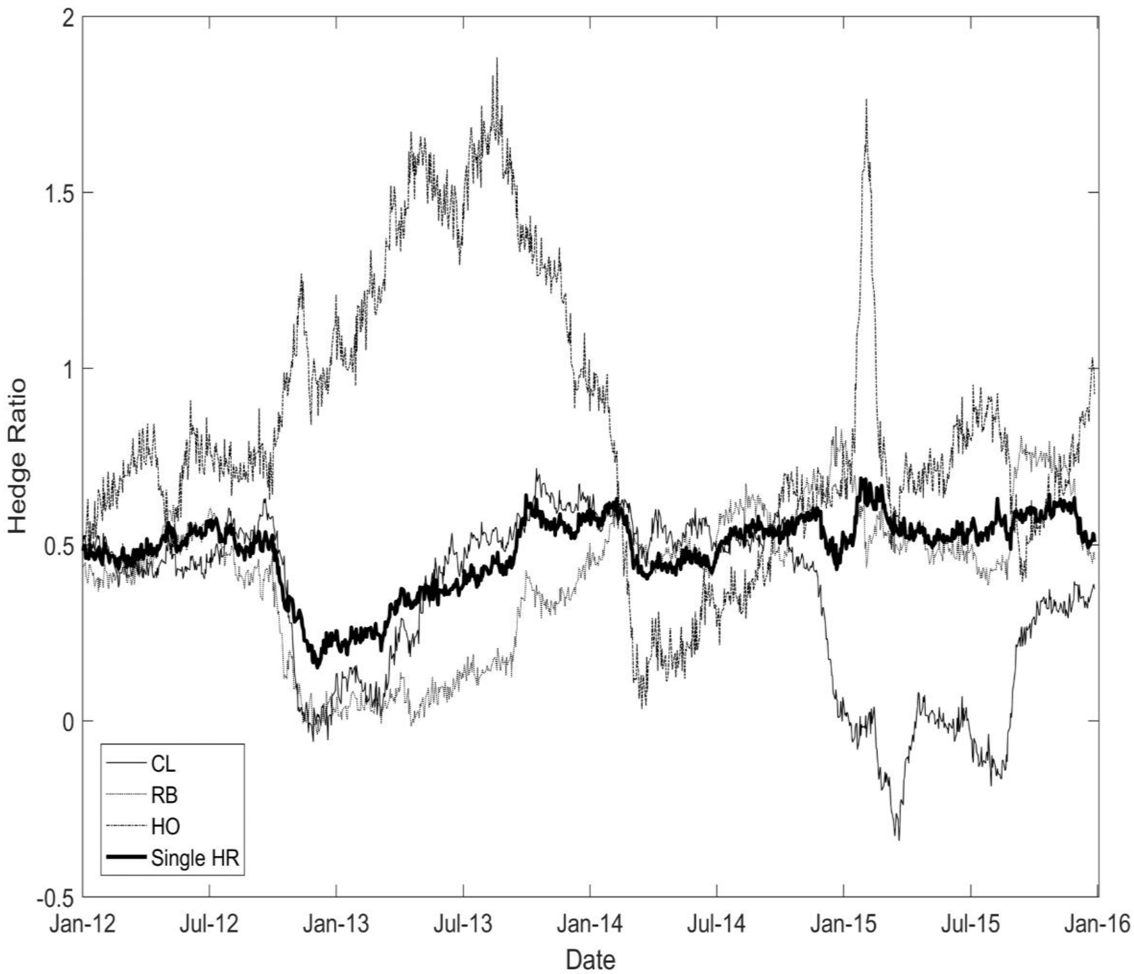


Figure A-4: Optimal hedge ratios under the MV criterion

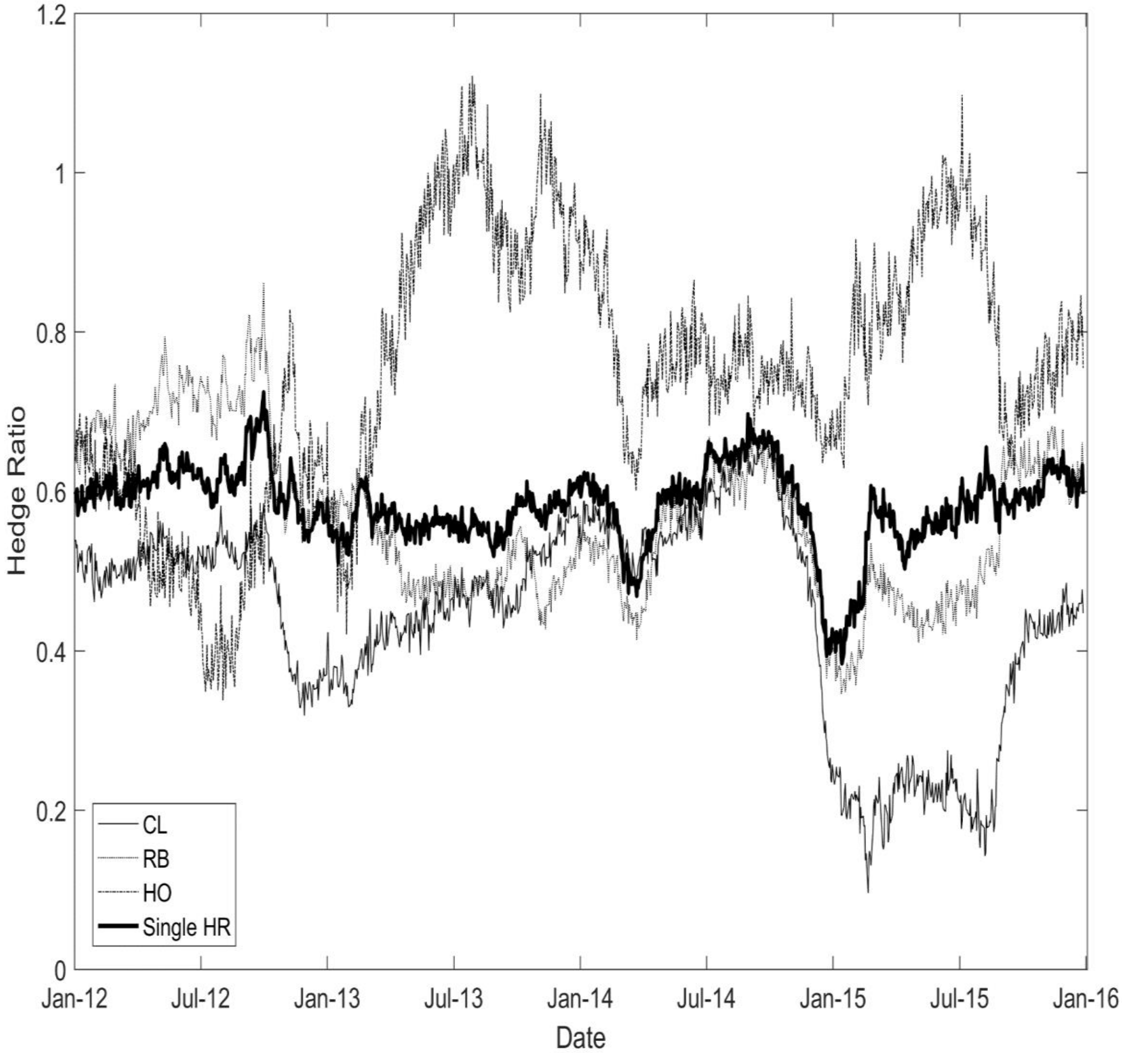


Figure A-5: Pairwise Kendall's τ for crude oil, gasoline, and heating oil futures prices, 250-day moving window

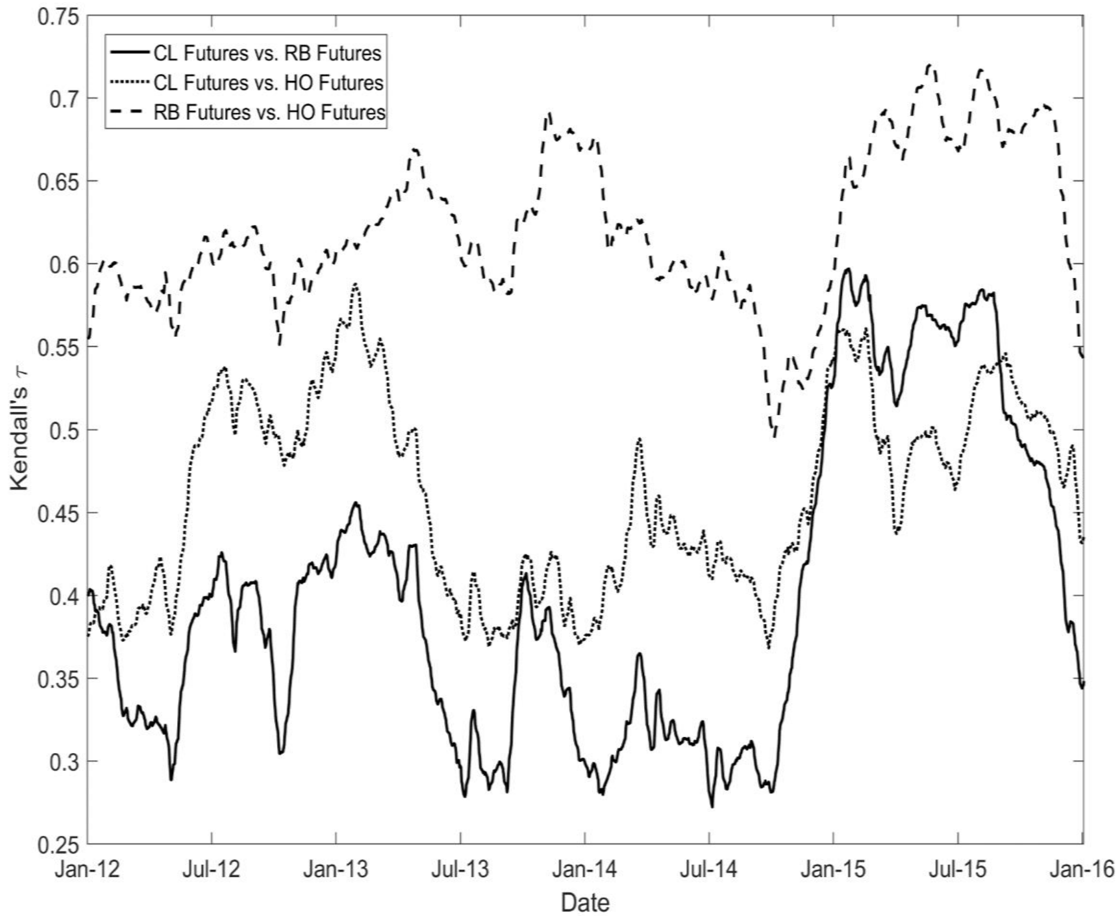


Figure A-6: Pairwise correlations for crude oil, gasoline, and heating oil futures prices, 250-day moving window

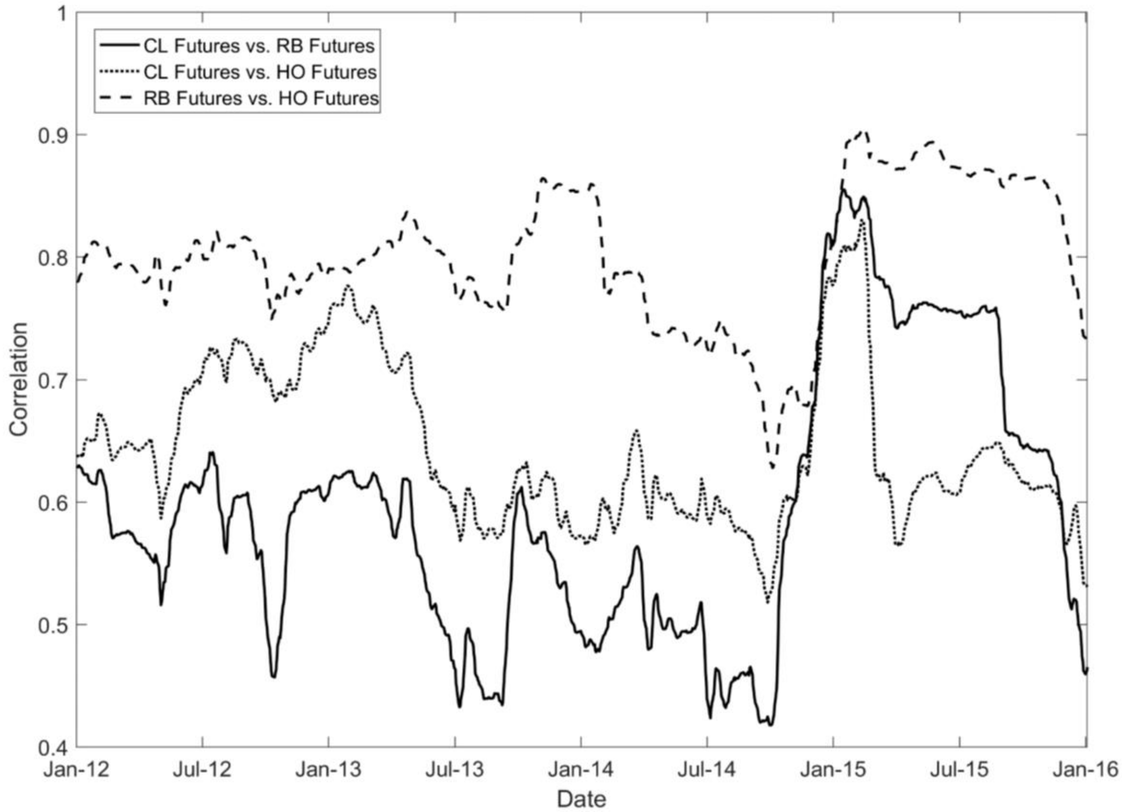


Figure A-7: U.S. Petroleum Administration for Defense Districts (Energy Information Administration, 2012)

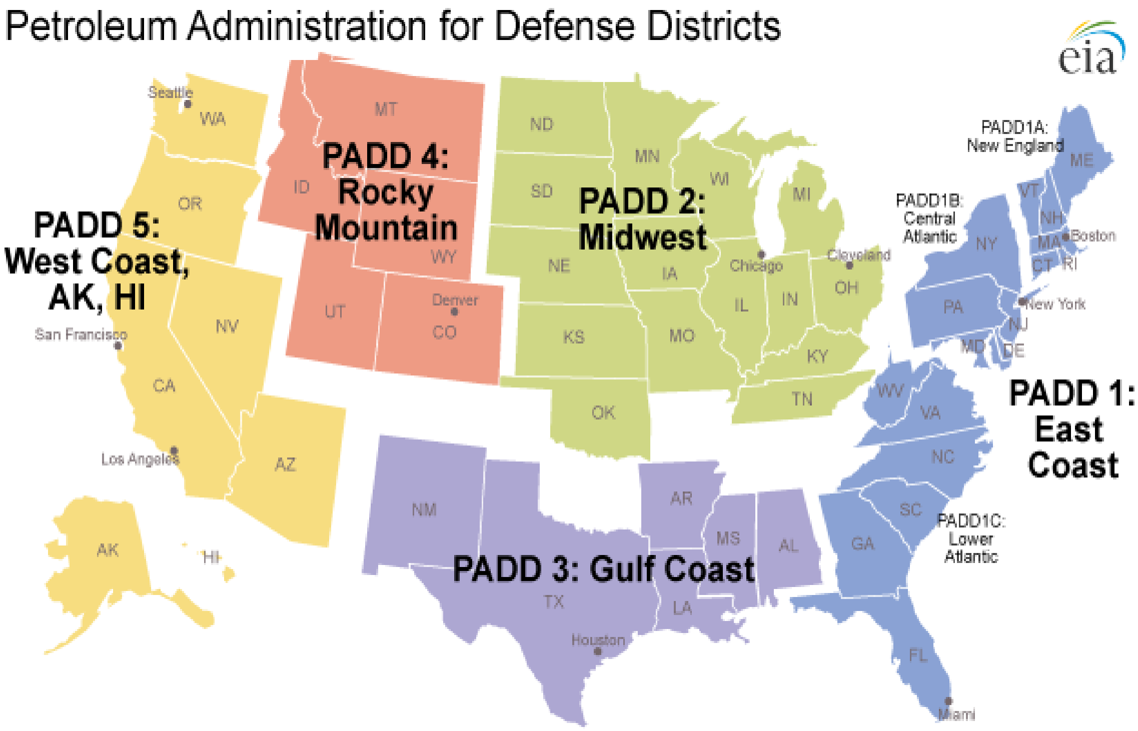


Figure A-8: WTI/Brent Price Spread (Jan 1994 - Mar 2016)

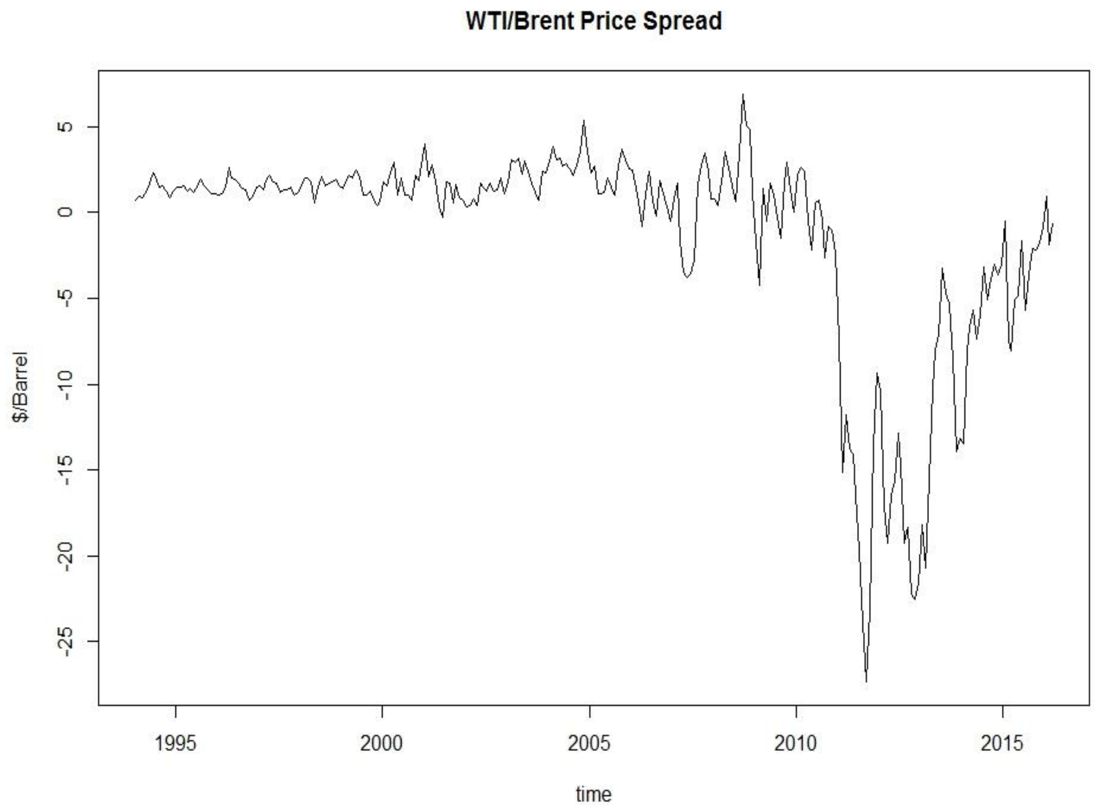


Figure A-9: Norway Production

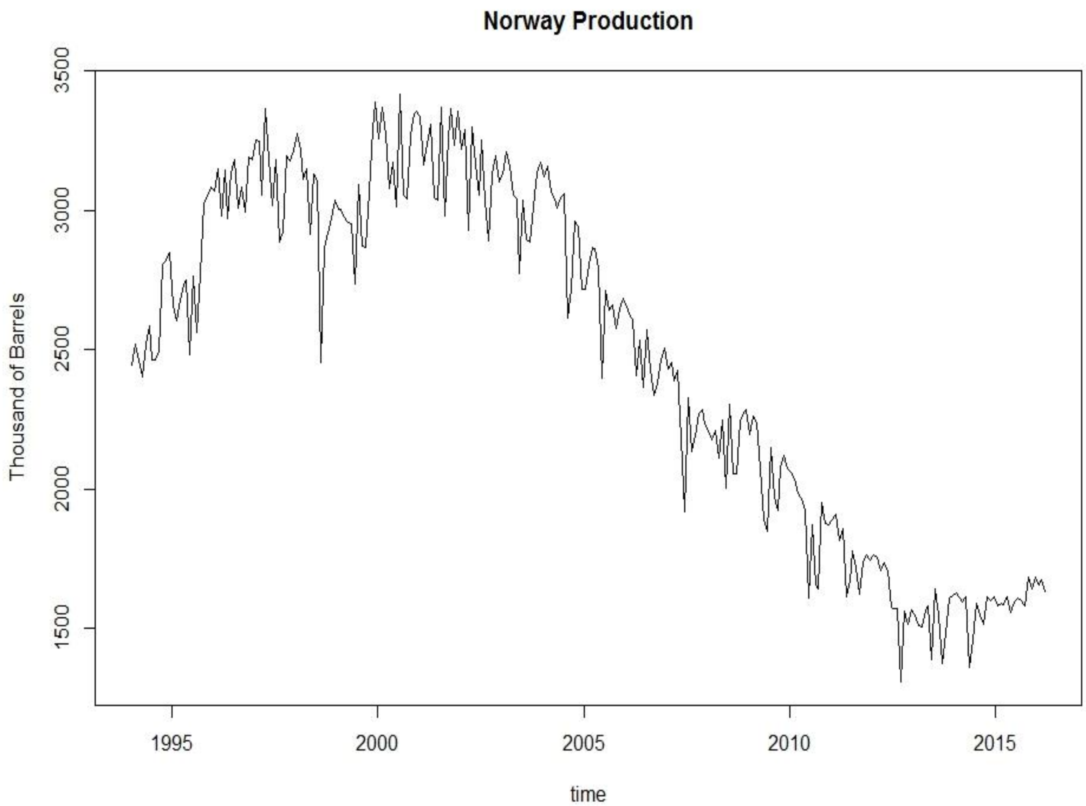


Figure A-10: U.S. Production

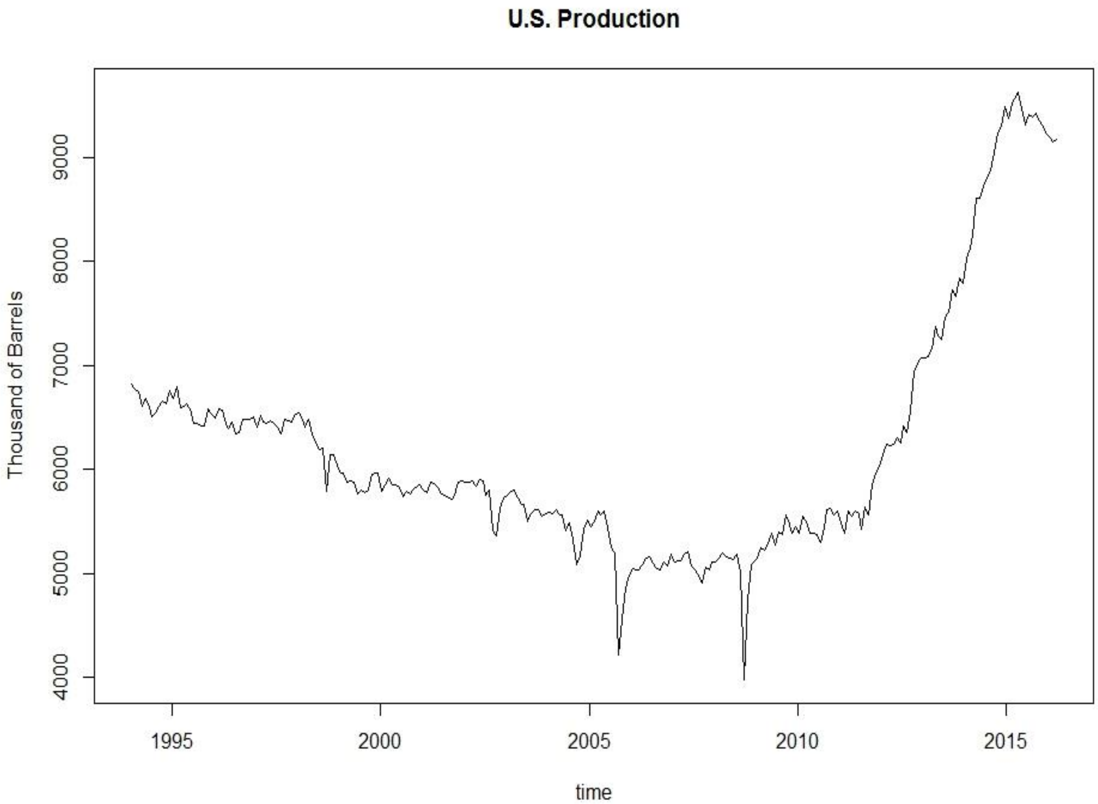


Figure A-11: ISM Purchasing Manager Index (PMI)

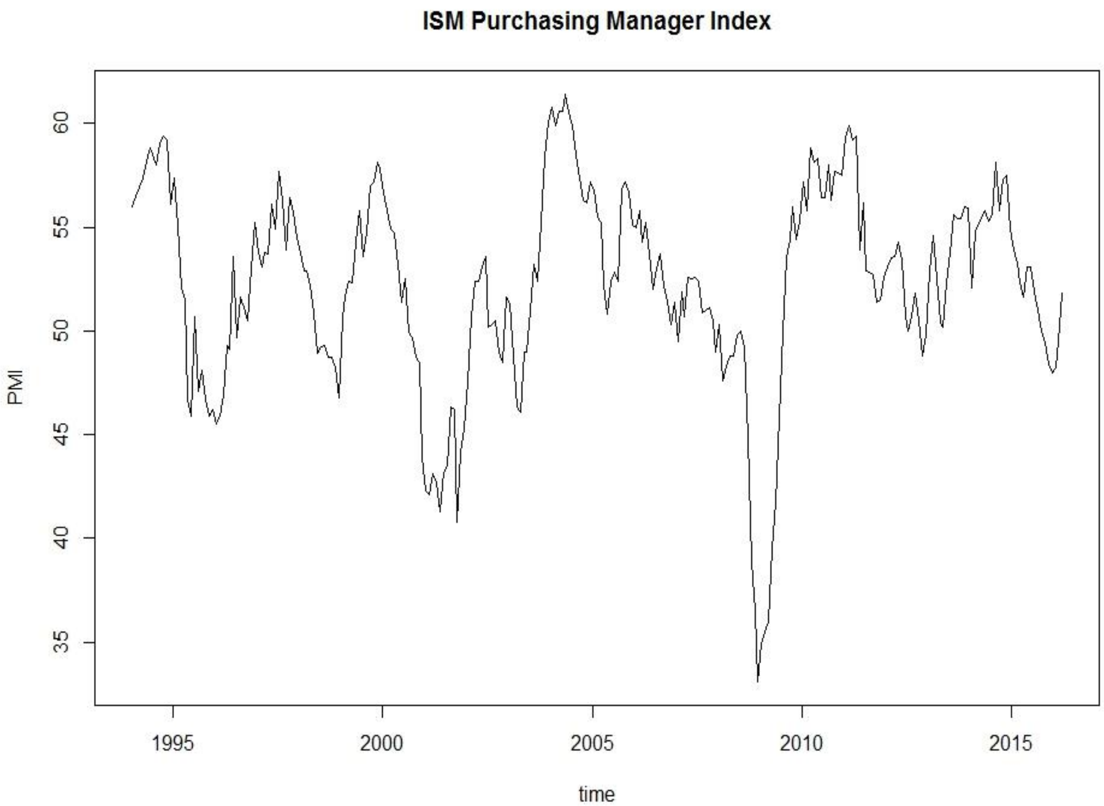


Figure A-12: PADD2 Inventory

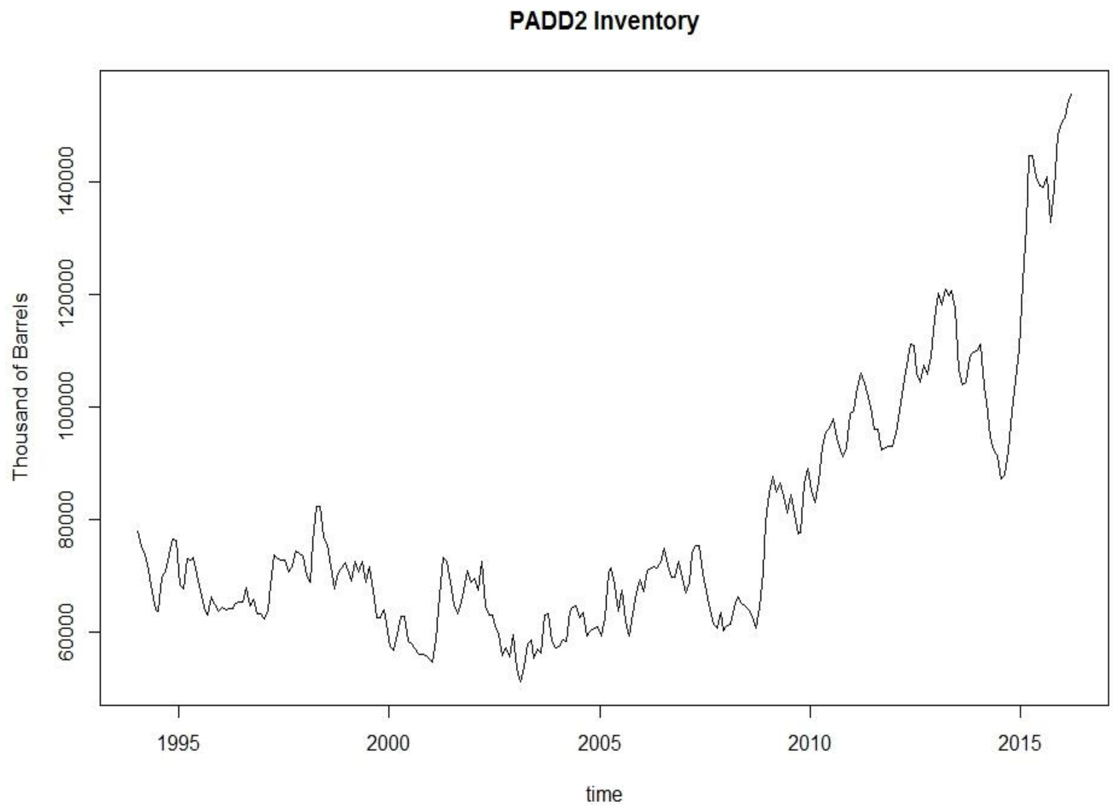


Figure A-13: Impulse Response Function Graphs: Norway Production Shocks (Jan 1994 – Nov 2010)

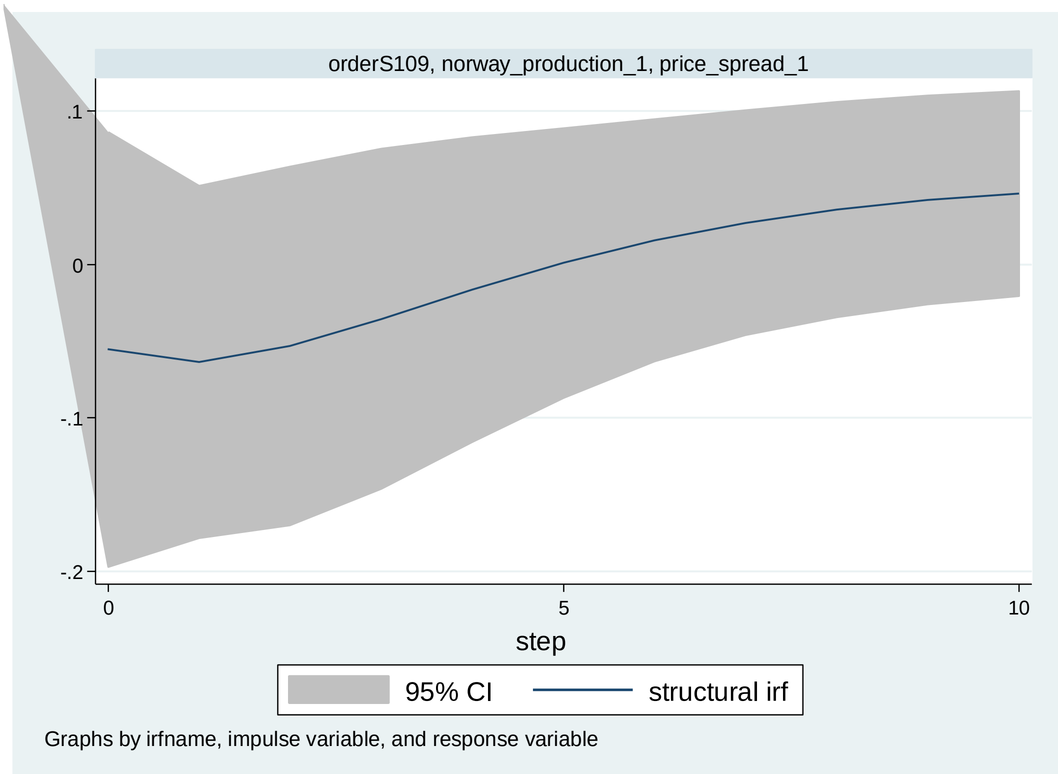


Figure A-14: Impulse Response Function Graphs: Norway Production Shocks (Dec 2010 – Mar 2016)

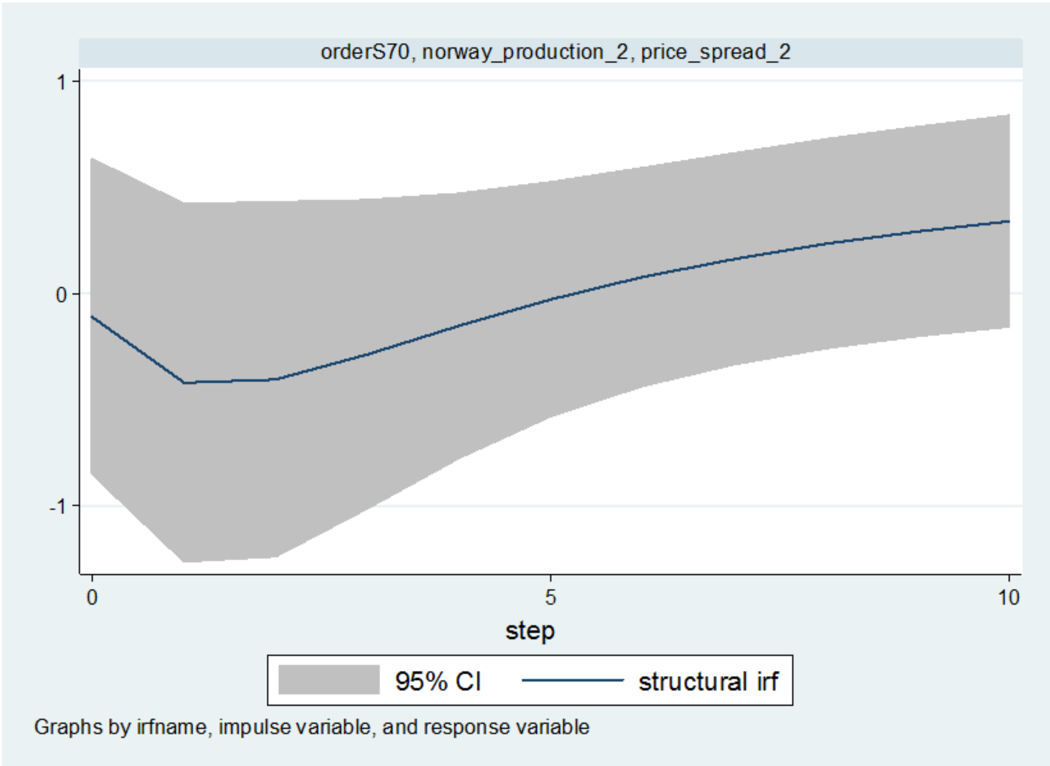


Figure A-15: Impulse Response Function Graphs: U.S. Production shocks (Jan 1994 - Nov 2010)

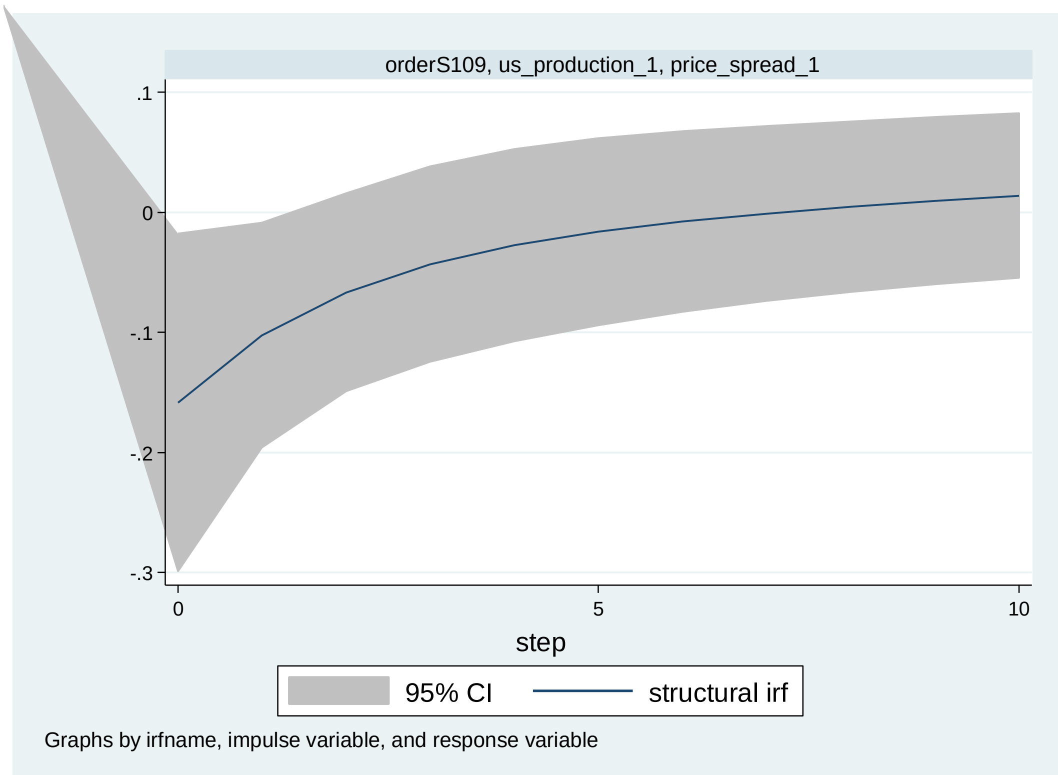


Figure A-16: Impulse Response Function Graphs: U.S. Production shocks (Dec 2010 - Mar 2016)

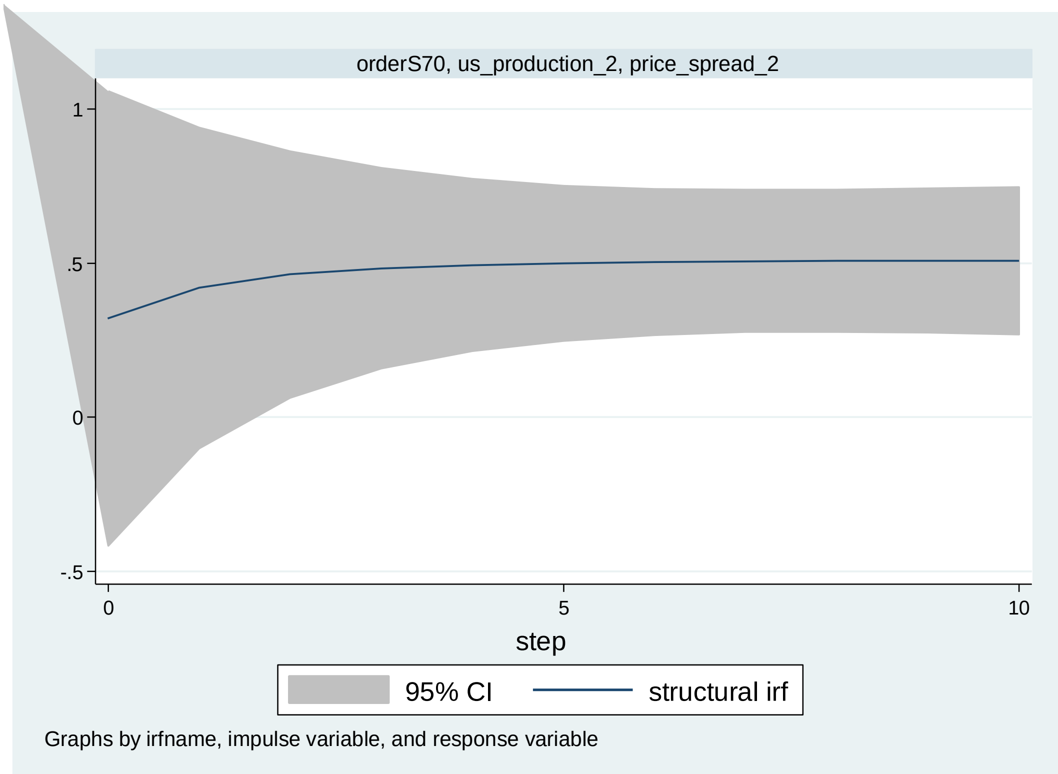


Figure A-17: Impulse Response Function Graphs: PMI Shock (Jan 1994 - Nov 2010)

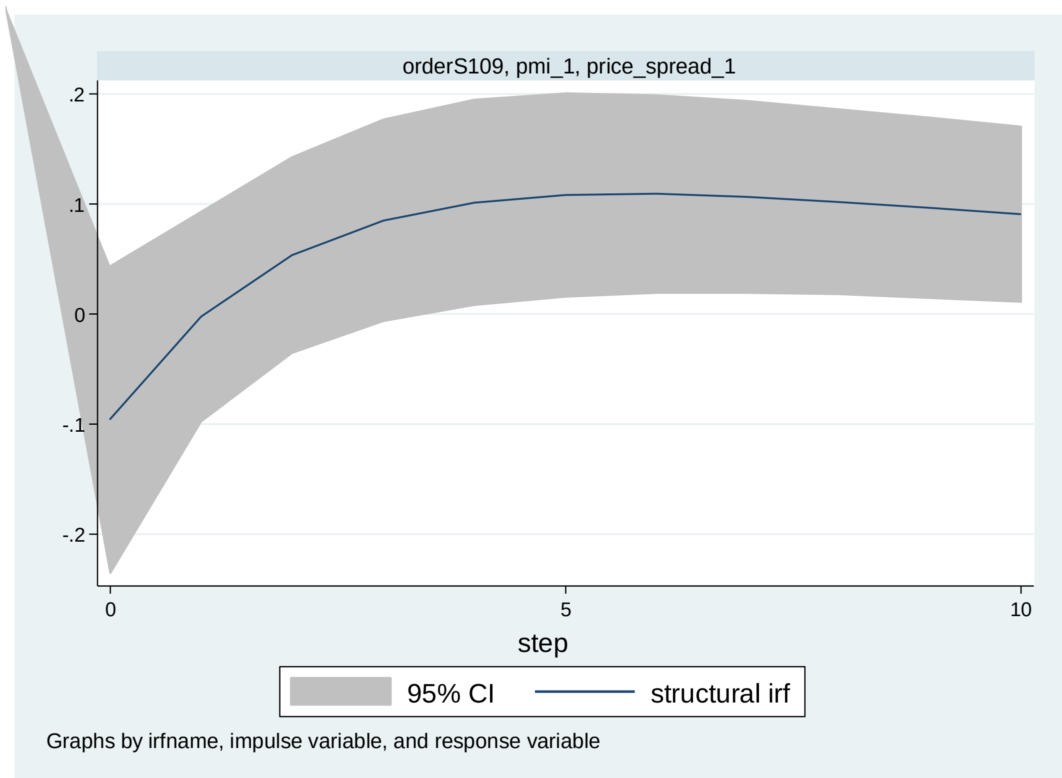


Figure A-18: Impulse Response Function Graphs: PMI Shock (Dec 2010 - Mar 2016)

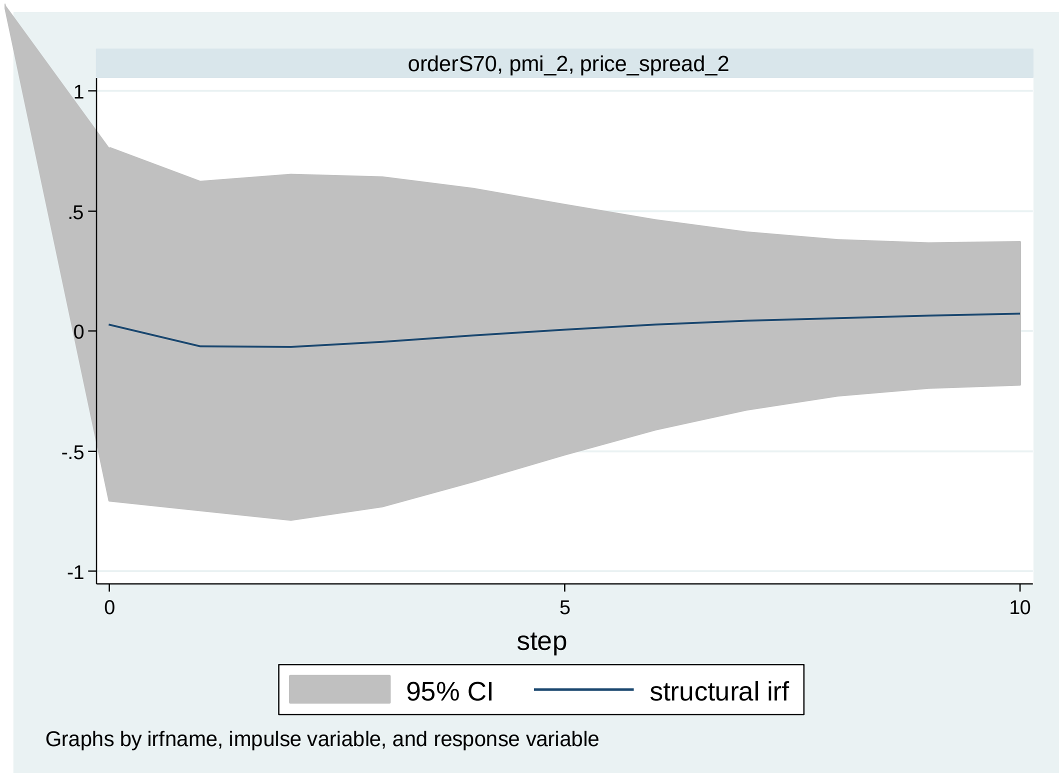


Figure A-19: Impulse Response Function Graphs: PADD2 Inventory (Jan 1994 - Nov 2010)

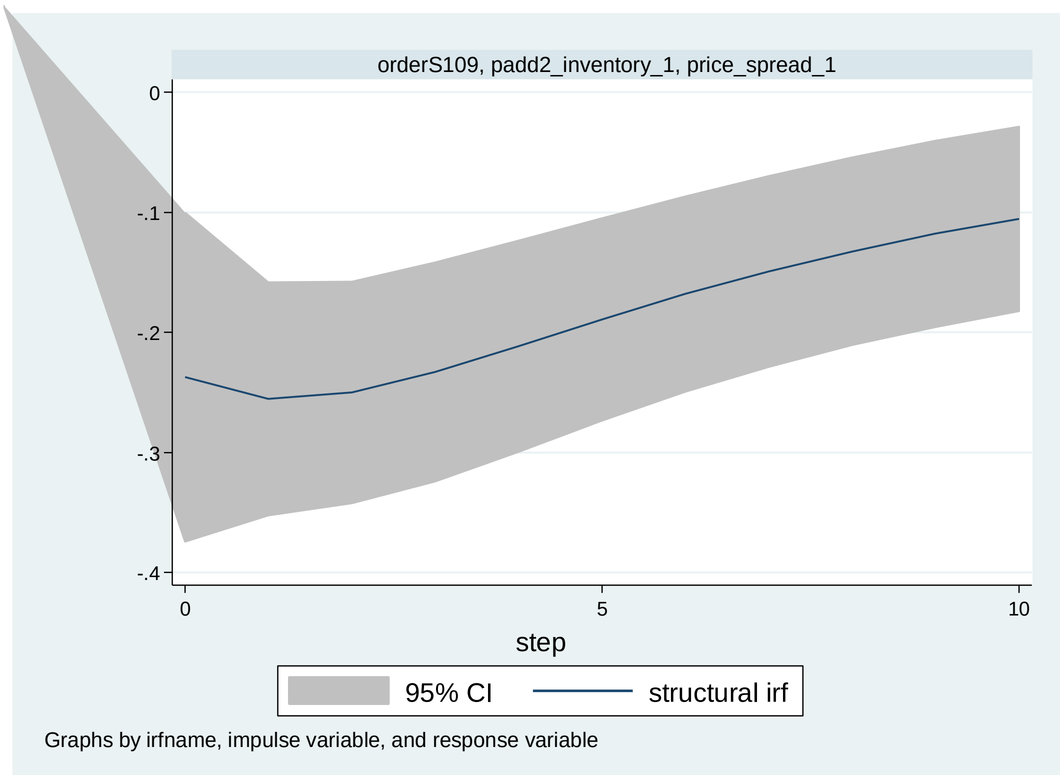


Figure A-20: Impulse Response Function Graphs: PADD2 Inventory (Dec 2010 - Mar 2016)

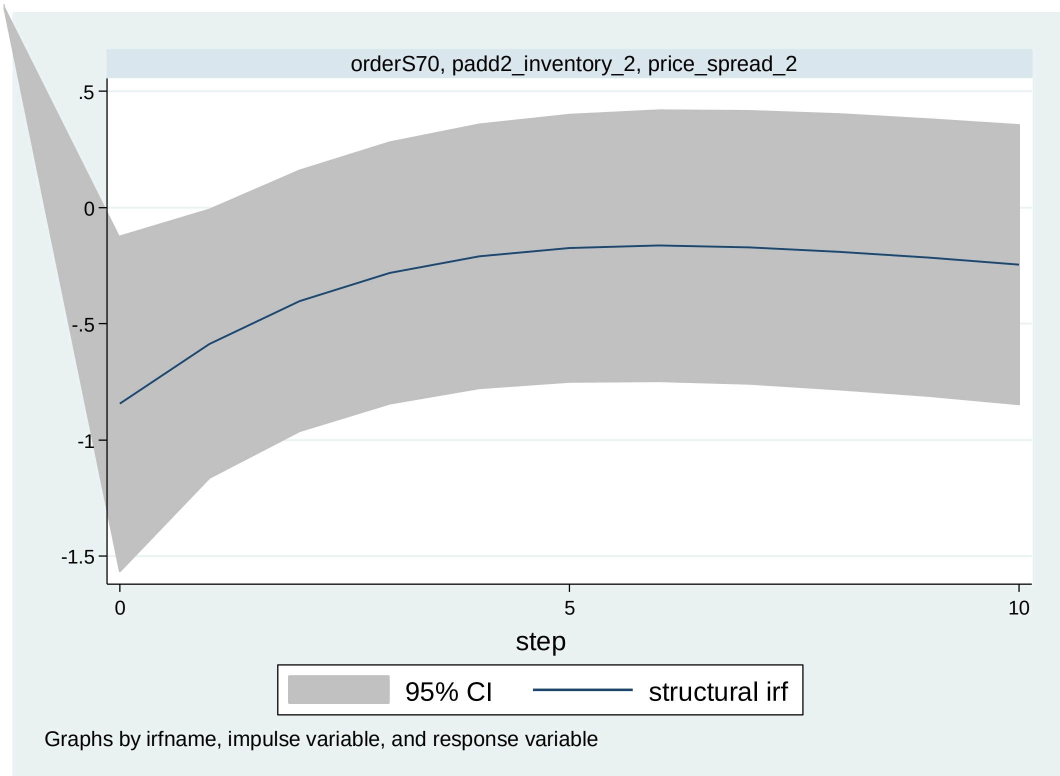


Figure A-21: Pairwise Dynamic Conditional Correlations (1)

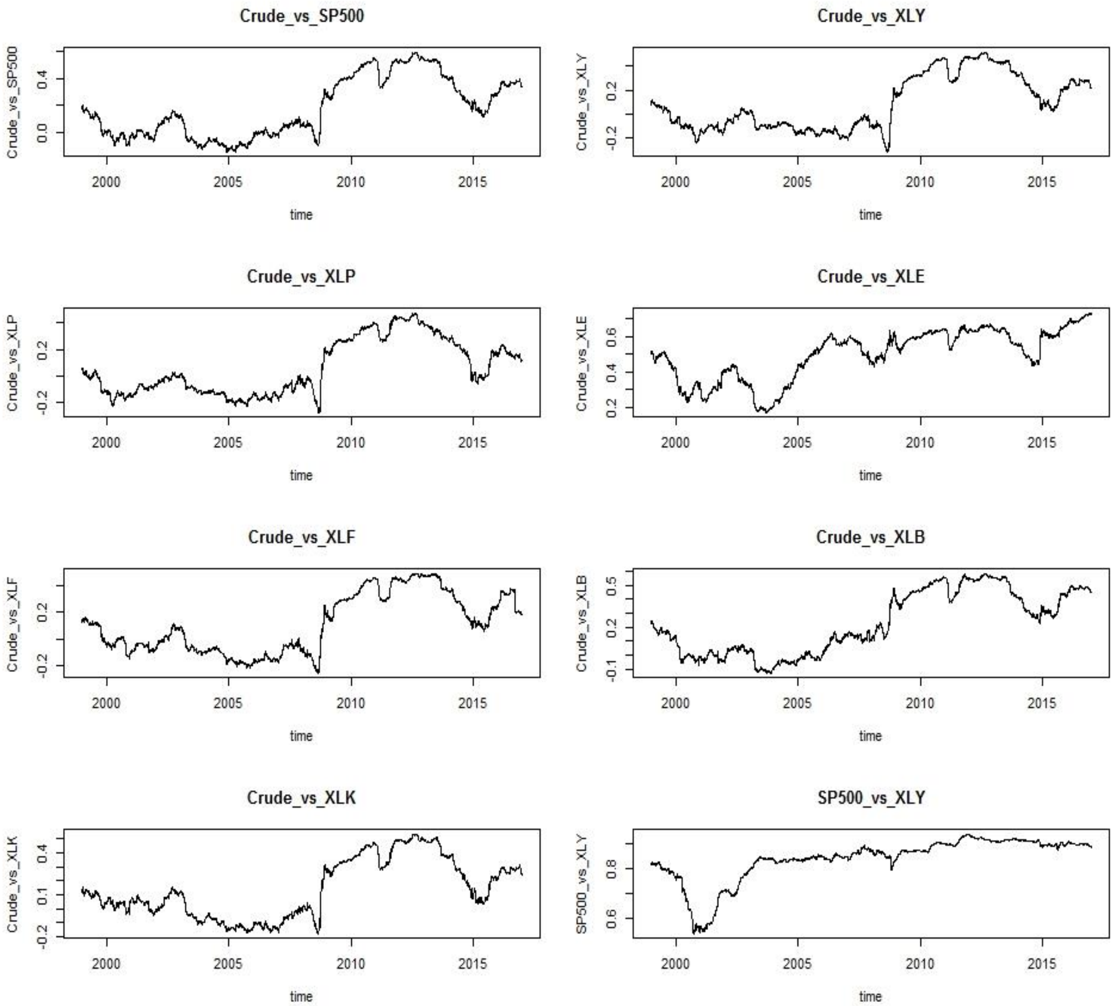


Figure A-22: Pairwise Dynamic Conditional Correlations (2)

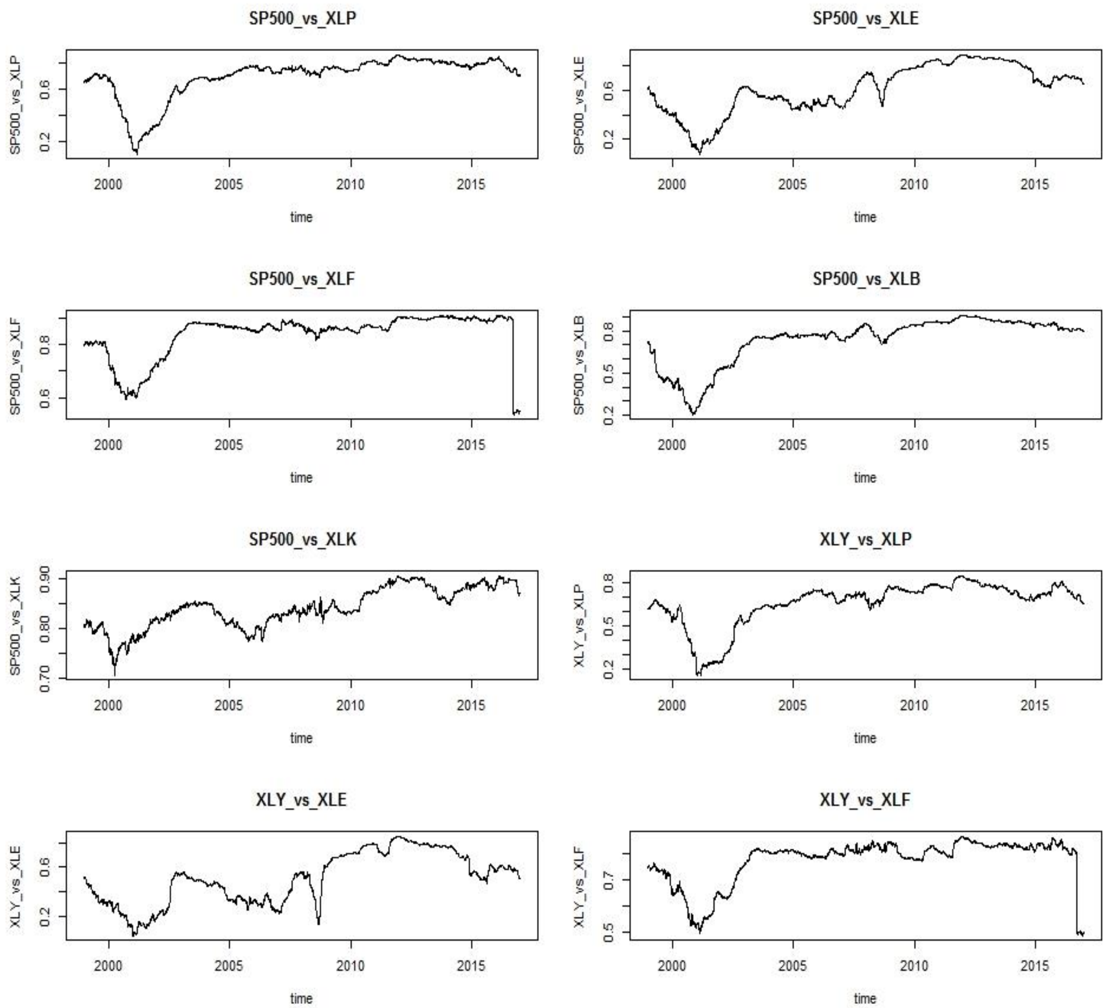


Figure A-23: Pairwise Dynamic Conditional Correlations (3)

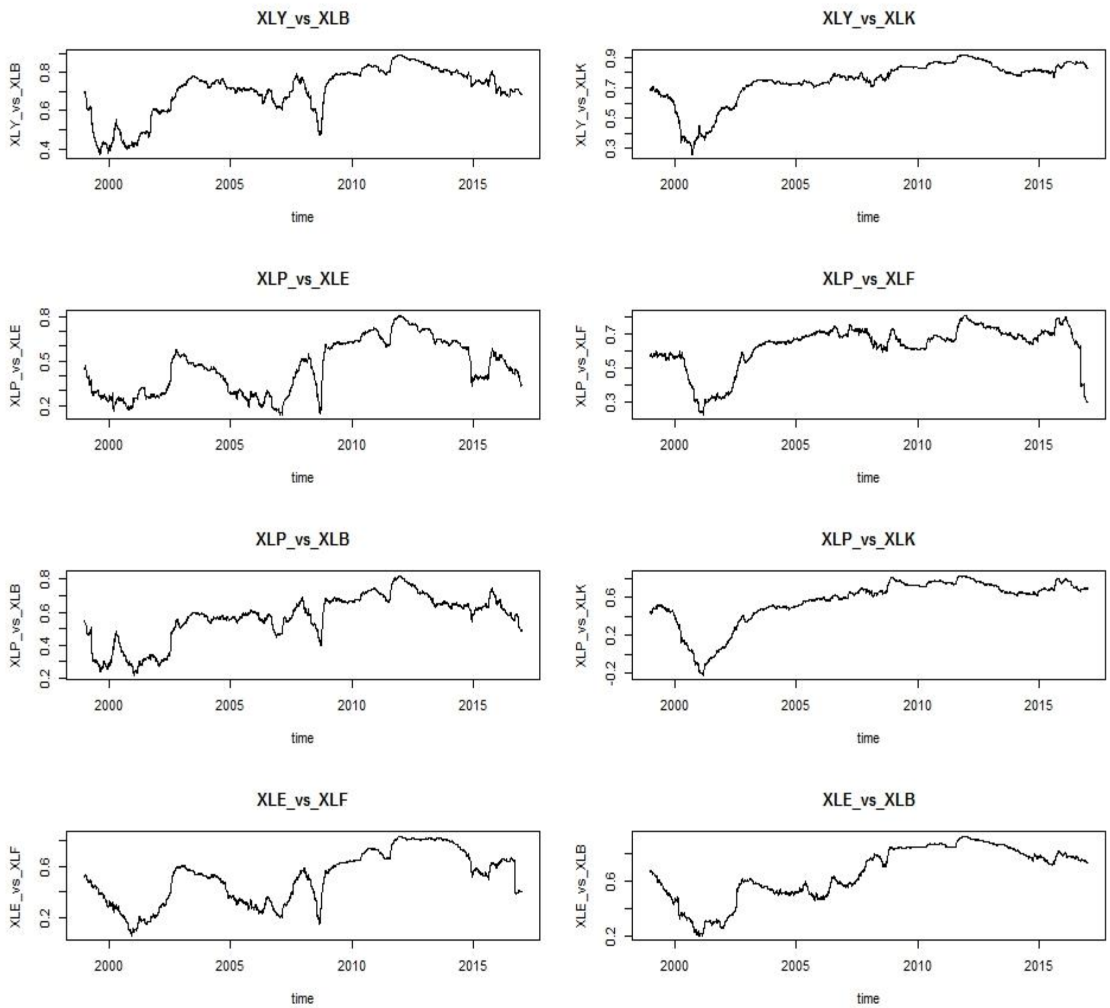


Figure A-24: Pairwise Dynamic Conditional Correlations (4)

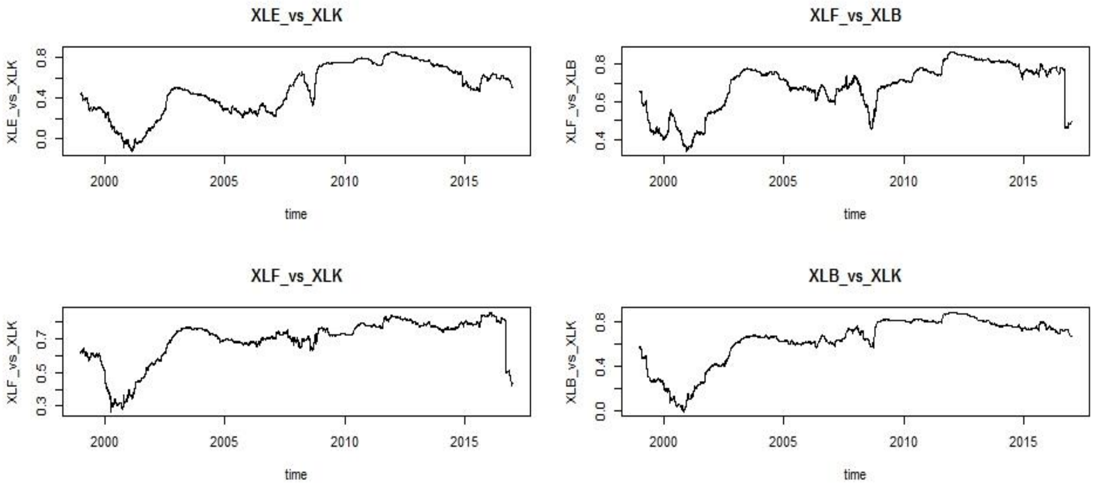


Figure A-25: Dynamic Net Volatility Spillover: Crude Oil

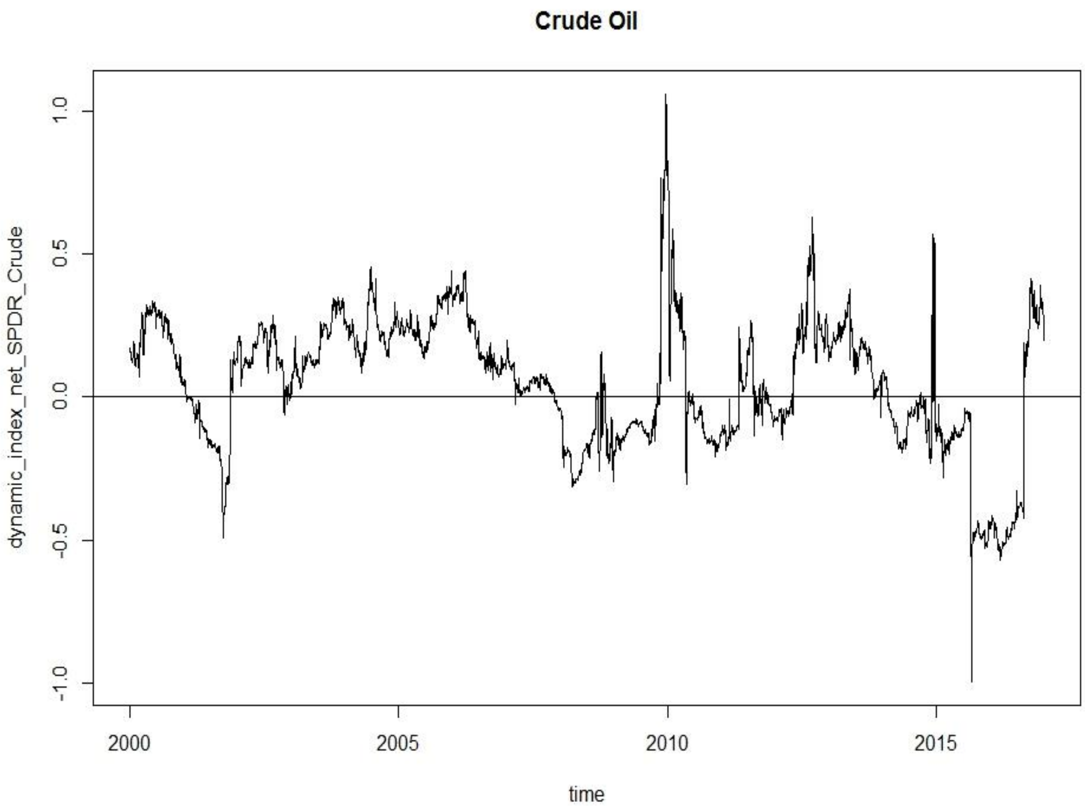


Figure A-26: Dynamic Net Volatility Spillover: S&P 500

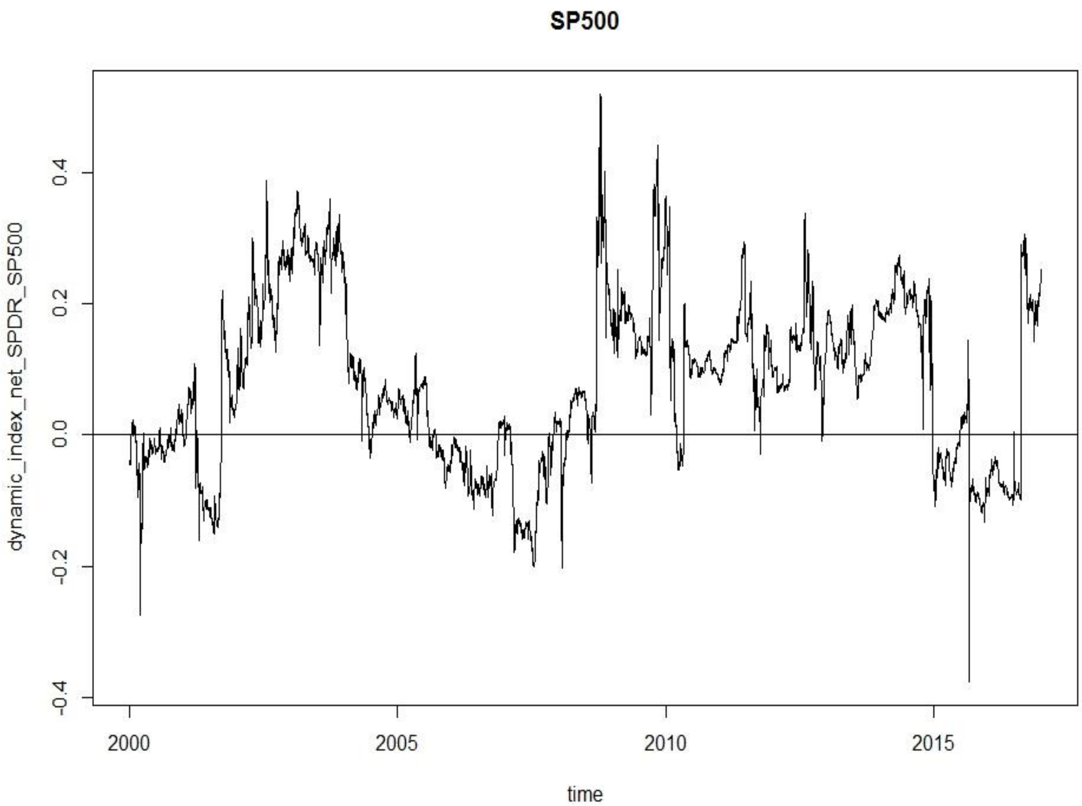


Figure A-27: Dynamic Net Volatility Spillover: Consumer Discretionary (XLY)

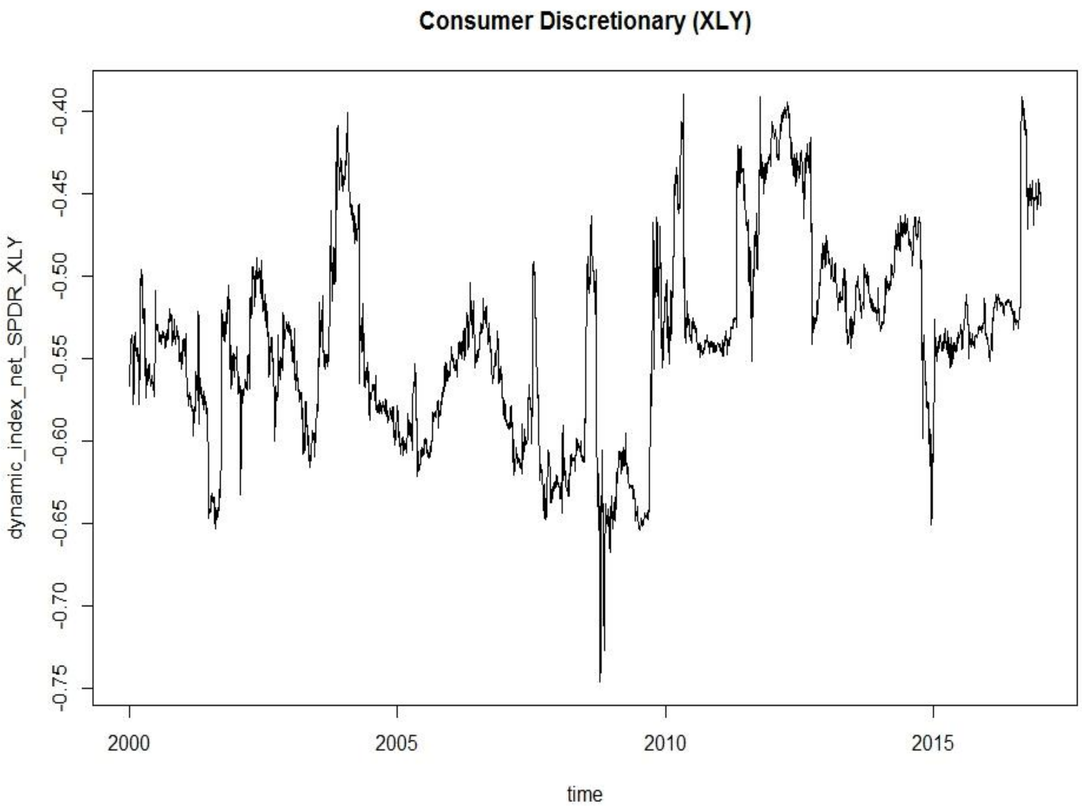


Figure A-28: Dynamic Net Volatility Spillover: Consumer Staples (XLP)

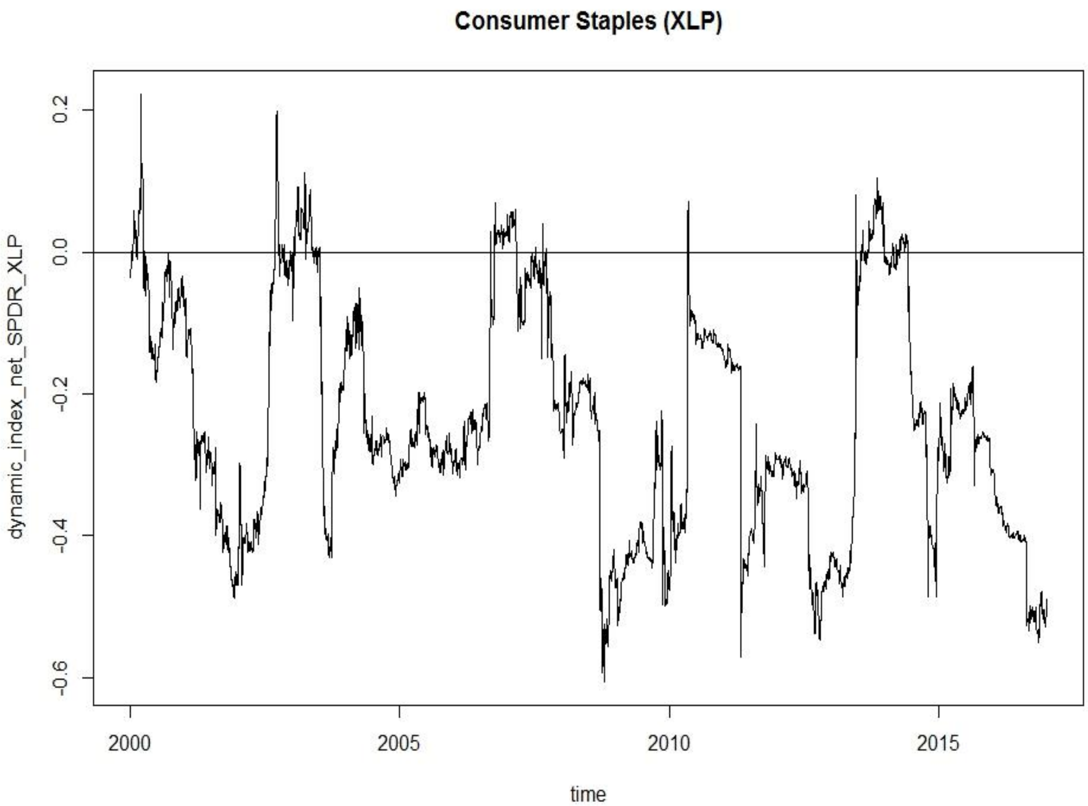


Figure A-29: Dynamic Net Volatility Spillover: Energy (XLE)

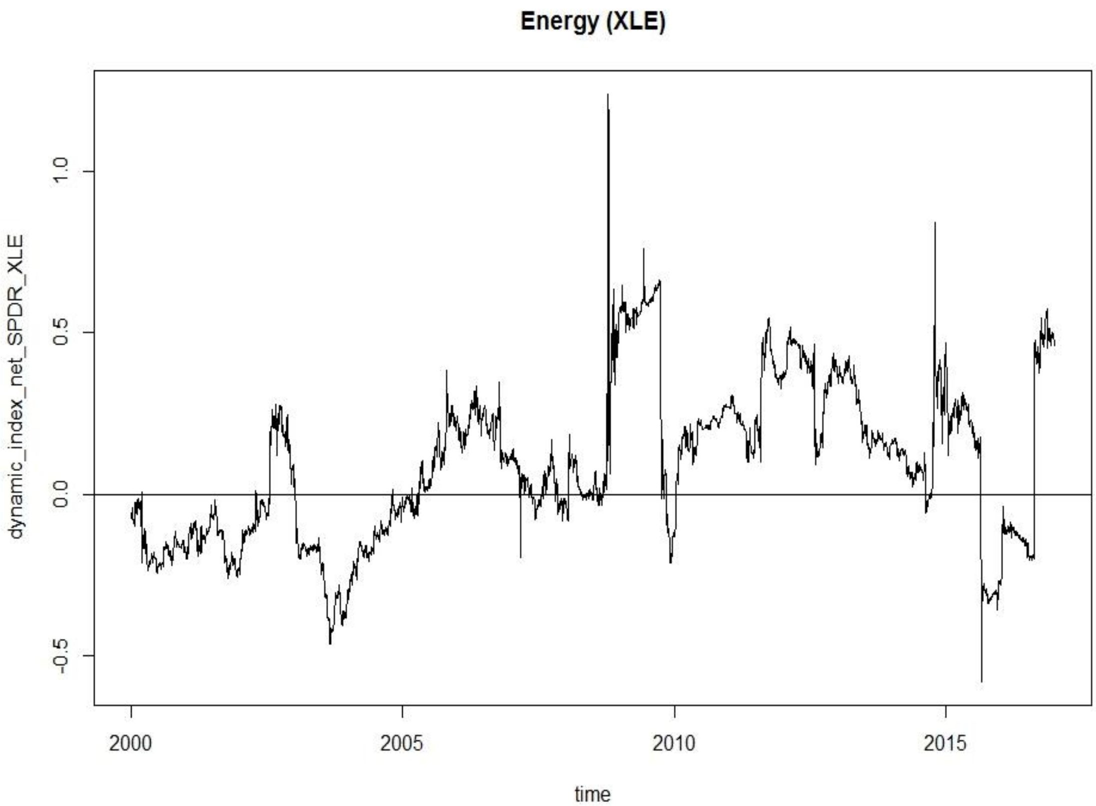


Figure A-30: Dynamic Net Volatility Spillover: Financials (XLF)

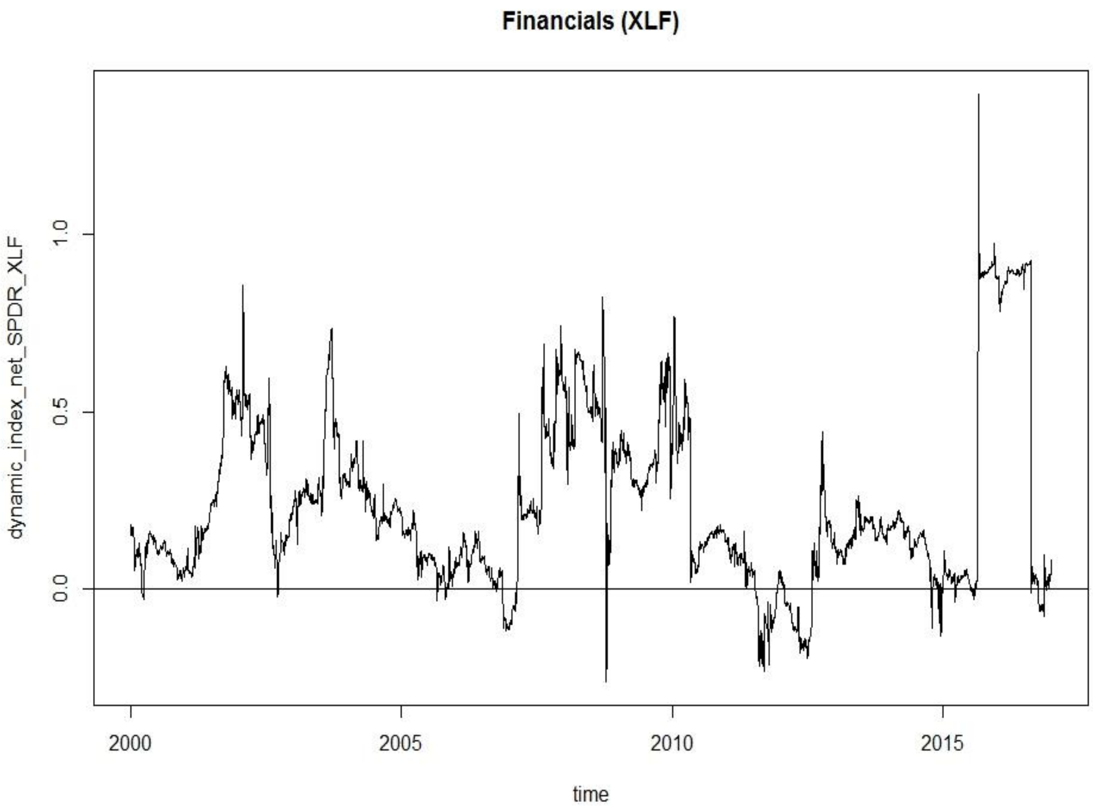


Figure A-31: Dynamic Net Volatility Spillover: Materials (XLB)

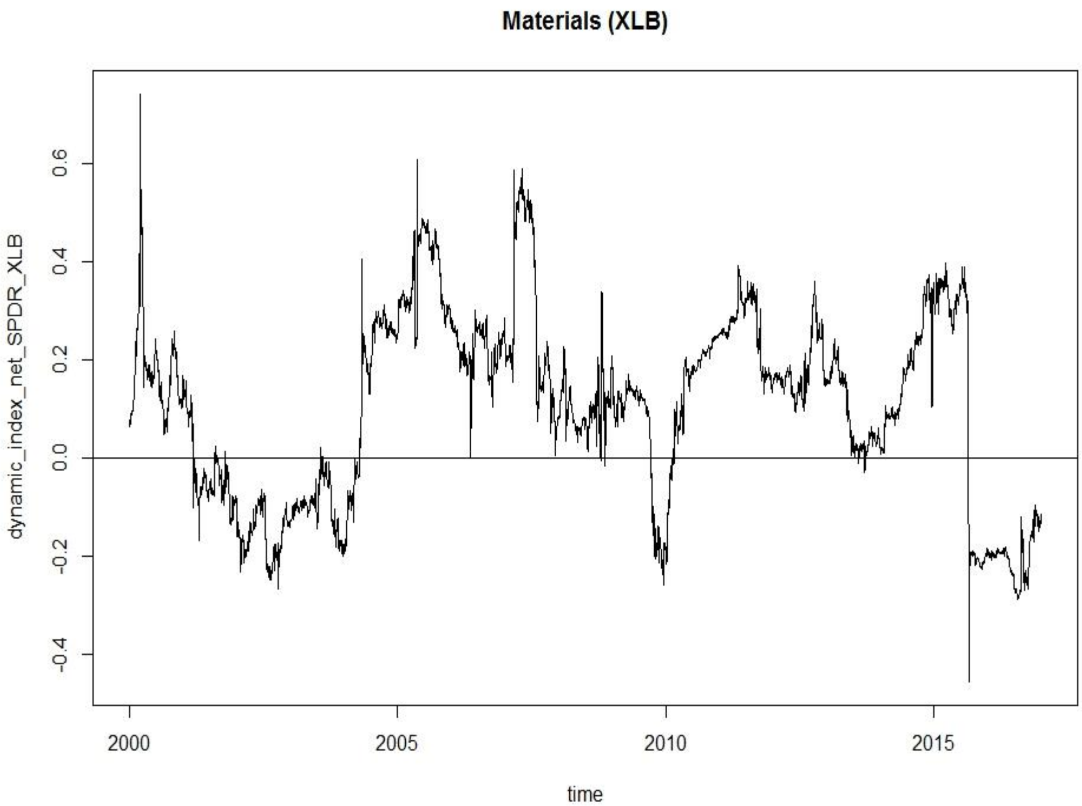
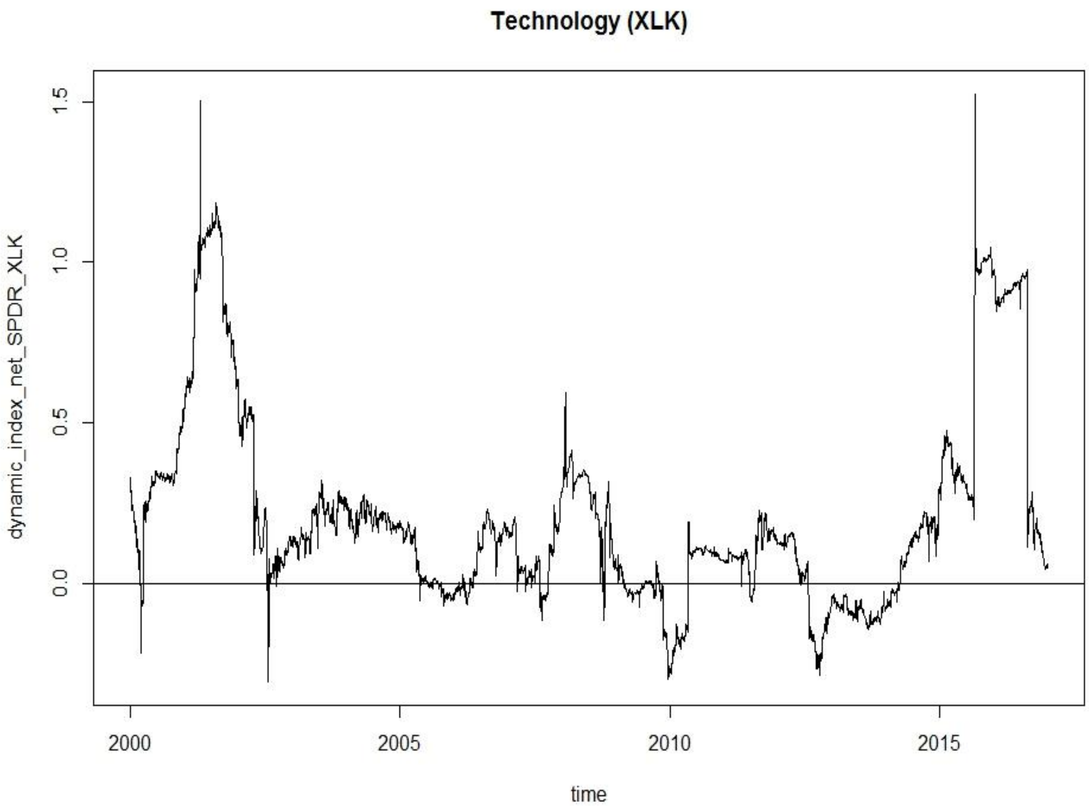


Figure A-32: Dynamic Net Volatility Spillover: Technology (XLK)



APPENDIX B.

TABLES

Table B-1: Unit root tests of spot and futures prices and shocks (log returns) for crude oil, gasoline, and heating oil between 01/01/2012 and 12/31/2015, in $/bbl

			Prices		Shocks	
			ADF	PP	ADF	PP
Crude Oil (CL)	Spot	test statistics	-1.287[10]	-3.301	-5.468[10]	-132.810
		p-value	0.880	0.921	<0.01***	<0.01***
	Futures	test statistics	-1.309[10]	-3.254	-5.418[10]	-130.160
		p-value	0.871	0.923	<0.01***	<0.01***
Gasoline (RB)	Spot	test statistics	-2.410[10]	-11.147	-6.535[10]	-87.319
		p-value	0.405	0.488	<0.01***	<0.01***
	Futures	test statistics	-2.229[10]	-8.891	-6.443[10]	-86.926
		p-value	0.481	0.614	<0.01***	<0.01***
Heating Oil (HO)	Spot	test statistics	-1.735[10]	-6.296	-7.590[10]	-80.348
		p-value	0.690	0.759	<0.01***	<0.01***
	Futures	test statistics	-1.507[10]	-5.269	-6.653[10]	-70.782
		p-value	0.787	0.816	<0.01***	<0.01***

Note: (1) ADF: Augmented Dickey–Fuller test. PP: Phillips–Perron test. The number of lags in the ADF regressions is given into brackets. (2) For both ADF test and PP test, the null hypothesis is the time series under test being nonstationary. * (resp. **, ***) denotes rejection of the null hypothesis at the 10% (resp. 5%, 1%) significance level.

Table B-2: Descriptive statistics of spot and futures shocks (log returns) for crude oil, gasoline, and heating oil between 01/01/2012 and 12/31/2015, in $/bbl

	Crude Oil (CL)		Gasoline (RB)		Heating Oil (HO)	
	Spot	Futures	Spot	Futures	Spot	Futures
2012						
Mean	-0.004	-0.005	0.003	0.022	0.003	0.002
SD	0.044	0.044	0.074	0.059	0.05	0.05
Skewness	-0.143	-0.147	-0.623	-0.011	-0.142	-0.135
Kurtosis	2.809	2.814	3.123	2.37	2.746	2.703
Minimum	-0.126	-0.126	-0.279	-0.098	-0.123	-0.119
Maximum	0.112	0.109	0.149	0.18	0.132	0.139
Pearson's Correlation	0.997		0.784		0.966	
Kendall's τ	0.951		0.616		0.831	
2013						
Mean	0.004	0.002	0	0.004	-0.001	0.001
SD	0.036	0.036	0.05	0.052	0.038	0.04
Skewness	0.008	0.018	0.26	0.142	-0.152	-0.272
Kurtosis	2.961	2.968	2.944	3.189	2.442	2.647
Minimum	-0.092	-0.091	-0.112	-0.134	-0.102	-0.108
Maximum	0.109	0.109	0.133	0.149	0.079	0.081
Pearson's Correlation	0.996		0.944		0.968	
Kendall's τ	0.946		0.805		0.856	

Table B-2: Continued

	Crude Oil (CL)		Gasoline (RB)		Heating Oil (HO)	
	Spot	Futures	Spot	Futures	Spot	Futures
2014						
Mean	-0.023	-0.02	-0.032	-0.025	-0.025	-0.017
SD	0.052	0.052	0.075	0.062	0.056	0.051
Skewness	-1.141	-1.298	-1.108	-1.076	0.157	-0.079
Kurtosis	4.677	5.04	4.971	4.405	5.103	3.694
Minimum	-0.209	-0.211	-0.302	-0.246	-0.198	-0.18
Maximum	0.06	0.06	0.123	0.083	0.185	0.115
Pearson's Correlation	0.989		0.96		0.824	
Kendall's τ	0.91		0.814		0.722	
2015						
Mean	-0.016	-0.022	-0.013	-0.008	-0.036	-0.027
SD	0.079	0.078	0.088	0.078	0.103	0.093
Skewness	0.177	0.228	0.23	-0.075	0.264	0.442
Kurtosis	2.348	2.431	2.674	2.879	3.209	3.155
Minimum	-0.168	-0.175	-0.239	-0.239	-0.285	-0.251
Maximum	0.186	0.186	0.204	0.189	0.243	0.233
Pearson's	0.99		0.952		0.941	
Kendall's τ	0.921		0.82		0.847	

Table B-3: Percent differences in hedging effectiveness using vector hedge ratio and single hedge ratio (baseline) under different criteria (higher values are better).

Year	2012	2013	2014	2015
			LPM_2	
Min	0.07%	0.96%	0.00%	4.35%
Max	11.52%	14.36%	26.98%	38.14%
Mean	1.18%	6.05%	0.96%	15.56%
% positive	100	100	100	100
			MV	
Min	0.37%	0.66%	0.03%	2.29%
Max	3.39%	2.88%	3.84%	10.25%
Mean	1.19%	1.60%	0.40%	5.38%
% positive	100	100	100	100

Table B-4: Percent differences in expected profit using vector hedge ratio and single hedge ratio (baseline) under different criteria (higher values are better).

Year	2012	2013	2014	2015
			LPM_2	
Min	–0.08%	0.02%	–0.02%	0.16%
Max	0.57%	0.83%	0.80%	1.54%
Mean	0.12%	0.35%	0.10%	0.69%
% positive	85.8	100	94.3%	100%
			MV	
Min	–0.24%	–0.08%	–0.10%	0.13%
Max	0.15%	0.26%	0.24%	0.63%
Mean	–0.07%	0.05%	–0.01%	0.38%
% positive	18.0%	78.2%	33.7%	100%

Table B-5: Percent differences in expected shortfall at 5% using vector hedge ratio and single hedge ratio (baseline) under different criteria (lower values are better).

Year	2012	2013	2014	2015
			LPM_2	
Min	–0.50%	–0.57%	–1.49%	–1.94%
Max	0.11%	–0.05%	0.03%	0.11%
Mean	–0.04%	–0.26%	–0.12%	–0.66%
% negative	61.7%	100.0%	81.2%	93.4%
			MV	
Min	–0.53%	–0.40%	–0.76%	–1.19%
Max	0.31%	0.02%	0.21%	0.03%
Mean	–0.05%	–0.21%	0.00%	–0.58%
% negative	60.5%	98.5%	29.5%	98.1%

Table B-6: Regression analysis of LPM2 optimal hedge ratios on measures of dependence (Kendall's τ) between spot and futures log returns.

	Hedge Ratio		
	Crude oil (CL)	**Gasoline (RB)**	**Heating Oil(HO)**
Intercept	-4.862***	2.799***	2.160*
Tau_CL.S_vs_RB.S	4.469**	9.320***	7.837**
Tau_CL.S_vs_HO.S	-9.831***	6.097***	-5.761*
Tau_CL.S_vs_CL.F	6.252***	-3.266***	0.090
Tau_CL.S_vs_RB.F	1.076	-14.807***	-5.820
Tau_CL.S_vs_HO.F	-2.892	-12.379***	-7.361**
Tau_RB.S_vs_HO.S	-0.621	0.042	-0.363
Tau_RB.S_vs_CL.F	-7.870***	-11.027***	-8.682***
Tau_RB.S_vs_RB.F	1.447***	2.893***	-2.056***
Tau_RB.S_vs_HO.F	1.821***	1.130**	2.434**
Tau_HO.S_vs_CL.F	7.464***	-4.234**	-1.323
Tau_HO.S_vs_RB.F	1.646**	-0.739	7.339***
Tau_HO.S_vs_HO.F	-0.313	-1.319***	-0.150
Tau_CL.F_vs_RB.F	0.687	14.846***	6.969*
Tau_CL.F_vs_HO.F	3.692*	11.549***	12.891***
Tau_RB.F_vs_HO.F	-3.143***	-0.696	-7.659***
Adjusted R-Squared	87.8%	89.1%	88.7%

Note: (1) *** = significant at 0.001 level, ** = significant at 0.01 level, * = significant at 0.05 level

Table B-7: Regression analysis of MV optimal hedge ratios on measures of dependence (Pearson correlations) between spot and futures log returns.

	Hedge Ratios		
	Crude oil (CL)	**Gasoline (RB)**	**Heating Oil(HO)**
Intercept	4.183***	8.207***	-0.291
Corr_CL.S_vs_RB.S	4.494***	5.905***	-5.954***
Corr_CL.S_vs_HO.S	1.723***	3.918***	-0.461
Corr_CL.S_vs_CL.F	-4.138***	-6.862***	1.333
Corr_CL.S_vs_RB.F	-4.396***	-5.005***	4.112**
Corr_CL.S_vs_HO.F	-3.562***	-2.453***	2.839**
Corr_RB.S_vs_HO.S	0.294	0.988***	1.066***
Corr_RB.S_vs_CL.F	-5.278***	-6.397***	6.227***
Corr_RB.S_vs_RB.F	1.038***	1.511***	-2.654***
Corr_RB.S_vs_HO.F	-0.480**	-1.226***	0.782**
Corr_HO.S_vs_CL.F	-1.954***	-2.461***	-1.340
Corr_HO.S_vs_RB.F	-0.418*	-0.119	-1.130***
Corr_HO.S_vs_HO.F	0.263**	-1.473***	1.456***
Corr_CL.F_vs_RB.F	4.024***	4.696***	-3.885**
Corr_CL.F_vs_HO.F	3.975***	1.401*	-2.444*
Corr_RB.F_vs_HO.F	0.246	-0.262	1.079**
Adjusted R-Squared	0.940	0.862	0.862

Note: (1) *** = significant at 0.001 level, ** = significant at 0.01 level, * = significant at 0.05 level

Table B-8: Unit-root Test of WTI and Brent Price Series

		Price in level		Price after first-difference	
		ADF	PP	ADF	PP
WTI	Test Statistic	-1.83[6]	-13.39	-7.17[6]	-161.45
	p-value	0.65	0.36	<0.01	<0.01
Brent	Test Statistic	-1.71[6]	-10.08	-6.72[6]	-161.84
	p-value	0.70	0.54	<0.01	<0.01

Note: (1) Number of lags for each ADF test is shown in the brackets following the test statistics.

Table B-9: Co-integration Test of WTI and Brent Price Series in Sub-samples

		Without a trend		With a trend	
		Trace statistic	5% Critical Value	Trace statistic	5% Critical Value
Sub-sample 1	r=0	55.34	15.41	67.75	18.17
	r≤1	2.71*	3.76	14.31	3.74
Sub-sample 2	r=0	9.96*	15.41	23.23	18.17
	r≤1	0.29	3.76	5.36	3.74

Table B-10: Descriptive Statistics of Norway Production, U.S. Production, PMI, PADD2 Inventory and WTI/Brent Price Spread

	Norway	U.S. Production	PMI	PADD2	WTI/Brent
Full Sample					
Min	1310	3980	33.10	51340	-27.31
Max	3417	9627	61.40	155700	6.88
Mean	2483	6199	52.23	79250	-1.35
Standard	622.74	1165.539	4.91	22514.1	6.22
Skewness	-0.27	1.479002	-0.99	1.449604	-2.12
Kurtosis	-1.38	4.722562	1.70	4.588146	3.87
Sub-sample 1					
Min	1611	3980	33.10	51340	-4.23
Max	3417	6817	61.40	98100	6.88
Mean	2755	5760	51.86	68610	1.445
Standard	443.51	564.179	5.34	9184.064	1.45
Skewness	-0.59	-0.006090053	-0.88	0.9801663	-0.79
Kurtosis	-0.72	2.438773	1.04	3.961301	3.86
Sub-sample 2					
Min	1310	5390	48.00	87340	-27.31
Max	1911	9627	59.90	155700	0.98
Mean	1621	7593	53.40	113000	-10.20
Standard	119.34	1456.851	2.90	18682.39	7.22
Skewness	0.09	-0.04096682	0.26	0.8446772	-0.46
Kurtosis	0.80	1.517343	-0.40	2.589429	-0.89

Table B-11: Descriptive Statistics for Daily Return Series

	Crude	S&P500	XLY	XLP	XLE	XLF	XLB	XLK
Min(%)	-16.5445	-10.3637	-12.3580	-6.2132	-15.5997	-20.1500	-13.2527	-9.0510
Max(%)	16.4097	13.5577	9.3265	6.6590	15.2503	27.3000	13.1534	14.9300
Mean(%)	0.0312	0.0113	0.0232	0.0144	0.0242	-0.0019	0.0146	0.0057
Std.dev.(%)	2.4341	1.2462	1.4368	0.9714	1.7617	2.0319	1.5677	1.6587
Skewness	-0.1241	-0.0327	-0.2270	-0.1221	-0.3976	0.0845	-0.1109	0.2545
Kurtosis	6.7898	12.6491	8.3902	7.2299	11.5794	24.9099	8.2766	8.8887
ARCH-LM	156.83 (1) ***	841.04 (2) ***	367.68 (2) ***	208.92 (1) ***	836.71 (2) ***	469.46 (1) ***	143.48 (1) ***	383.17 (2) ***

Note: (1) For ARCH-LM test of Engle (1982), numbers in the parentheses are lag orders. Lag length chosen by SC. (2) *** denotes the rejection of the null hypotheses of no autoregressive conditional heteroscedasticity (ARCH) effect at 1% significance level.

Table B-12: Unit Root Tests for Daily Return Series

	Crude	S&P500	XLY	XLP	XLE	XLF	XLB	XLK
ADF	-15.47***	-16.113***	-16.076***	-16.545***	-17.382***	-16.423***	-16.68***	-15.138***
PP	-4488.4***	-4374***	-4211.3***	-4352.9***	-4321.9***	-4541.5***	-4378.7***	-4344.5***
KPSS	0.27151***	0.20417***	0.15389***	0.29861***	0.068924***	0.08248***	0.03808***	0.31454***

Note: (1) Lags of ADF test are included in the parenthesis following the test statistics. (2) *** indicates rejection of the null hypothesis of unit root for ADF and PP test and of stationarity for KPSS test at 1% significance level

Table B-13: Summary Statistics for Pairwise Dynamic Conditional Correlations (1)

	Crude_vs_SP500	Crude_vs_XLY	Crude_vs_XLP	Crude_vs_XLE	Crude_vs_XLF	Crude_vs_XLB	Crude_vs_XLK
Min	-0.1484	-0.3128	-0.2768	0.1710	-0.2553	-0.1285	-0.1799
Max	0.5962	0.5184	0.4772	0.7348	0.4902	0.5860	0.5371
Mean	0.1768	0.0914	0.0620	0.4983	0.1101	0.2294	0.1401
Median	0.1201	0.0324	-0.0097	0.5341	0.0863	0.1742	0.0871
Pearson's correlation	0.2014	0.1030	0.0529	0.4917	0.1253	0.2409	0.1259
Kendall's τ	0.1159	0.0595	0.0379	0.3517	0.0691	0.1587	0.0803

Table B-14: Summary Statistics for Pairwise Dynamic Conditional Correlations (2)

	SP500_vs_XLY	SP500_vs_XLP	SP500_vs_XLE	SP500_vs_XLF	SP500_vs_XLB	SP500_vs_XLK	XLY_vs_XLP
Min	0.5371	0.1088	0.0787	0.5352	0.2033	0.7057	0.1551
Max	0.9385	0.8611	0.8957	0.9132	0.9118	0.9073	0.8508
Mean	0.8366	0.6955	0.6166	0.8393	0.7360	0.8417	0.6595
Median	0.8596	0.7476	0.6344	0.8673	0.7805	0.8387	0.7088
Pearson's correlation	0.8438	0.6785	0.6883	0.8064	0.7643	0.8424	0.6158
Kendall's τ	0.6453	0.5013	0.4444	0.6602	0.5541	0.6672	0.4494

Table B-15: Summary Statistics for Pairwise Dynamic Conditional Correlations (3)

	XLY_vs_XLE	XLY_vs_XLF	XLY_vs_XLB	XLY_vs_XLK	XLP_vs_XLE	XLP_vs_XLF	XLP_vs_XLB
Min	0.0436	0.4867	0.3713	0.2616	0.1385	0.2260	0.2173
Max	0.8537	0.8691	0.8935	0.9194	0.8105	0.8129	0.8222
Mean	0.5093	0.7748	0.7031	0.7419	0.4570	0.6296	0.5670
Median	0.5161	0.8083	0.7309	0.7724	0.4535	0.6646	0.5886
Pearson's correlation	0.5374	0.7366	0.7016	0.6900	0.4652	0.5593	0.5409
Kendall's τ	0.3324	0.5611	0.4852	0.5187	0.2893	0.4219	0.3711

Table B-16: Summary Statistics for Pairwise Dynamic Conditional Correlations (4)

	XLP_vs_XLK	XLE_vs_XLF	XLE_vs_XLB	XLE_vs_XLK	XLF_vs_XLB	XLF_vs_XLK	XLB_vs_XLK
Min	-0.2223	0.0638	0.2027	-0.1224	0.3353	0.2668	-0.0147
Max	0.8325	0.8342	0.9270	0.8641	0.8684	0.8562	0.8925
Mean	0.5574	0.5139	0.6587	0.4898	0.6806	0.6903	0.6346
Median	0.6398	0.5373	0.7207	0.4986	0.7147	0.7241	0.6766
Pearson's correlation	0.4425	0.5376	0.6938	0.4611	0.6443	0.5985	0.5673
Kendall's τ	0.3607	0.3405	0.4665	0.3086	0.4726	0.4737	0.4207

Table B-17: Static/Full-Sample Connectedness Table

	Crude Oil	SP500	XLY	XLP	XLE	XLF	XLB	XLK	**From**
Crude Oil	79.87	2.96	1.59	1.12	5.37	4.09	2.63	2.37	20.13
SP500	1.21	23.80	5.74	8.34	10.61	19.32	12.48	18.50	76.20
XLY	1.45	15.99	11.96	7.83	11.20	21.74	14.41	15.42	88.04
XLP	0.93	14.00	4.98	24.19	11.66	16.67	11.29	16.28	75.81
XLE	3.52	11.10	4.36	6.28	40.91	12.47	13.07	8.28	59.09
XLF	1.59	14.07	5.28	6.02	7.56	39.25	11.87	14.35	60.75
XLB	1.09	13.02	5.57	6.57	12.90	17.38	30.45	13.02	69.55
XLK	0.75	14.73	4.58	7.79	6.32	16.32	9.57	39.93	60.07
To	10.53	85.88	32.12	43.96	65.62	107.99	75.32	88.22	
From	20.13	76.20	88.04	75.81	59.09	60.75	69.55	60.07	
Net	-9.59	9.69	-55.92	-31.85	6.53	47.23	5.77	28.15	**63.70**

Note: (1) The “From” column is calculated as the row sum excluding the diagonal element (connectedness to its own), it gives the total directional connectedness from all others to variable i. (2) The “To” row is calculated as the column sum excluding the diagonal element (connectedness to its own), it gives the total directional connectedness from variable j to others. (3) The “Net” row is calculated as the difference between the “to” and “from” total directional connectedness. Positive (negative) values indicate that the variable is a net transmitter (receiver) of spillovers. (4)The number in bottom-right cell is the total connectedness.