Analysing the Connectedness between Crude Oil and Petroleum Products: Evidence from the USA

Abstract: This paper investigates the connectedness, in time and frequency domain, between daily returns series of crude oil and petroleum products for the period 2003/01/11-2018/03/12. In doing so, we have applied DY (2012) and BK (2018) spillover method. The overall spillover index value obtained from DY (2012) method is 62.29% and from BK method index value fluctuates with frequency. Further empirical evidence shows that the total connectedness, in time and frequency domain, as measured by a rolling-window approach, has dynamic and volatile characteristics. Our overall results show that there is a high level of partial contemporaneous relationship between jet fuel, heating oil, US gasoline as well as diesel. Furthermore, results from the Wavelet multiple correlations and cross-correlation show that heating oil act as a leader for a short time horizon, whereas gasoline at medium and longer time scale. The results from the DY spillover analysis suggest that among the series analysed heating oil has the highest contribution to others, which is confirmed across frequencies by BK spillover method (and the Brent contributes least to others at all frequency bands). These findings have important implications for a wide range of market participants, including investors, hedge funds, speculators, as well as for energy policy, with different temporal horizons.

Keywords: Generalized Variance Decomposition, Connectedness, Oil-Petroleum Products

1. Introduction

This paper enhances our understanding about the relationship between crude oil prices and petroleum products (heating oil, diesel, jet fuel, propane and gasoline) using the USA context. The existing energy literature documents strong co-movements between crude oil prices and petroleum products (Liu et al. 2010, Tong et al. 2013, Sun and Shi 2015). Volatility in crude oil prices has substantial implications on international capital markets and owing to its economic relevance. Prior research has extensively investigated the relationship between oil prices and stock return (Basher and Sadorsky 2006, Chen 2009, Driesprong et al. 2008, Filis 2010, Basher et al. 2012), oil prices and key traded assets (oil, gold and stock) (Baruník et al. 2016), oil prices and exchange rates volatility (Shahbaz et al. 2015, Roubaud and Arouri 2018, Nussairand Olson 2019), oil prices and inflation dynamics (Cerra 2017, Choi et al. 2018), oil prices and personal consumptions (Wang, 2013), oil prices and economic activities (Hamilton 1983), oil price volatility and unemployment (Rafiq et al. 2008), oil prices and the business cycle (Ponka and Zheng 2019) and, oil prices and economic growth (Cunado and De Gracia 2015, Troster et al. 2018). Researchers argue that demand and supply of crude oil are driven by speculation instead of key economic fundamentals (Sarwar et al. 2019). After the financial crisis, crude oil prices skyrocketed from $45 to $145 in July 2008, and in a couple of months later in December 2008, the oil prices experienced another dip to a low of around $30 (Reboredo, 2013). More recently, oil prices are experiencing another rise after a political confrontation between the United States and Iran, resulting the United States to walk out from its historic nuclear deal and imposing more strict economic sanctions limiting oil exports from Iran. While the impact of crude oil prices has been extensively investigated, the recent international events causing fluctuations in oil prices and its associated products have been attracting the attention of policymakers, consumers, firms, researchers and the society at large.

Rising crude oil prices are one of the critical determinants of refined petroleum products. Prior empirical studies in the UK (Bacon 1991) and USA (Borenstein et al. 1997) show that gasoline prices adjust more rapidly subsequently to any increases in crude oil prices. On the other hand, research on the directional causality of crude oil prices in the USA shows that crude oil shocks have 'lead impacts' on gasoline prices, and simultaneously, gasoline shocks' have a 'lag impact' on crude oil prices (Sita, and Abosedra, 2013). Although the USA context has been extensively debated in the energy literature and the determinants and impact of crude oil prices are well established in the empirical literature (as discussed in para 1). The relationship between crude oil prices and petrol products is inconclusive mainly for several reasons. First, from a theoretical perspective, the traditional pricing theory in economics and finance, which determine an equilibrium price and balancing the demand and supply, fails to explain and predict the pricing behaviour of crude oil and petroleum products (Lee and Zyren 2007). Second, the methodological approaches (GAARCH, restricted GARCH) used in prior studies capture the sources the impact of more than one source of variation. However, these methods strictly assume that sources of variations assume in oil prices to be independent, and this strict exogeneity assumption may not be valid in testing the relationship between oil prices and petroleum products. We, therefore, use more sophisticated econometric estimation, Diebold and Yilmaz (2012), hereafter DY (2012) Barunik and Krehlik (hereafter BK, 2017) that overcome some of the methodological concerns raised in prior empirical research.

Crude oil is an essential component of refined petroleum products. The empirical literature presents two critical hypotheses about the causal relationship between crude oil-petroleum products. The former argues that crude oil prices affect petroleum products prices (Frey and Manera, 2007), and the second set of hypothesis shows that, in principle, the marginal price of a petroleum product is ascertained by the highest marginal cost of crude oil used in the given product (Frey and Manera, 2007). Similarly, Kaufmann et al. (2009) examine the association between crude oil, prices of gasoline, inventory levels for oil and gasoline and the price of natural gas. They investigate how changes in crude oil prices are transmitted in the energy supply chain. Using weekly and quarterly data, they find that oil prices shock effect inventory level, prices of motor gasoline and these processes are transmitted gradually to the natural gas market. These studies, therefore, confirm an expected causal relationship between oil and petroleum products.

Our research contributes to the existing literature in following four ways: (i), Our chosen unusual period which covers several events resulting into higher energy prices (e.g., 2003 Iraq war, 2008 global financial crisis, and the 2011 Arab spring). (ii), this research is very timely following a recent debate about increasing energy prices after the United States walked out from Iran nuclear deal. (iii), The methodological approach, we apply, takes into account the dynamic relationship between oil prices and petroleum products. (iv), We believe that the causal relationship between oil prices and petroleum products is not simple and straightforward. Our sophisticated spillover indices (using DY, and BK estimations) uncover the underlying degree of interdependence between oil prices and petroleum products in the context of the United States. Using daily data from, and applying 2003/01/11 to 2018/03/12, and applying DY (2012) and BK (2018) spillover index We find a spillover index of 62.29% between crude oil and petroleum products.

The rest of the paper is organised as follows. Section 2 discusses relevant literature. Section 3 presents the methodology; Section 4 discusses empirical results, and finally, in section 5, we conclude the paper.

2. **Literature review**

Existing literature on oil prices and petroleum products is well documented in different countries and times period by applying different estimation approaches. Analysis of volatility and connectedness between oil and petroleum products prices provides useful insights about forecasting and risk management in the oil sector. Institutional investors, fund managers, and energy companies are in particular interest in the volatility of these two variables to develop robust assessment framework in managing their portfolio of assets (including energy products) (Frey and Manera 2007, Kaufmann et al. 2009).

After decades of research on energy prices, the relationship between oil prices and petroleum products is inconclusive. One of the shortcomings observed in prior empirical research is related to the underlying assumptions used in their estimation approaches (Asche et al. 2003). For instance, it is generally assumed that oil prices are exogenous and that any changes in crude oil prices are directly observed in petroleum products. This strict exogeneity assumption fails to consider the impact of changes in refined petroleum products prices on crude oil prices (Asche et al. 2003).

Although oil-producing countries (OPEC) have maintained their modest production capacity in the past few years, much attention is now given to non-OPEC countries such as the United States, where oil output is expected to grow by 3.7 million barrels per day, which is considered to be substantially higher than global production growth of 6.4 million barrels per day by the year 2023 (International Energy Agency, 2018). The US Department of Energy statistics reports that the US government has paid an amount of $25 billion in maintaining a capacity of over 700 million barrels of World largest government-owned stockpile of emergency crude oil (known as Strategic Petroleum Reserves) (U.S. Office of Fossil Energy, 2017b). This provides some justification for our chosen country context–the United States.

Uncertainty in crude oil prices and its associated refined petroleum products has significant negative implications for corporate investment decisions (Herriques and Sadrosky 2011, Phan et al. 2018). Firms may postpone or limit their investment following increasing oil prices. While increasing crude oil prices may push up the cost of production, rising oil prices may also reduce consumer expenditures and demand for oil-related products, including refined petroleum products (Hamilton, 2009). Using 33,000 firms from 54 countries for the period 1984–2015, Phan et al. (2018) find that volatility and uncertainty in crude oil prices negatively affect corporate investment and firm valuations.

Prior empirical research has largely used linear econometric approaches in understanding the transmission of oil prices into other related energy prices, including petroleum products. The seminal work of Borenstein et al. (1997) confirms that gasoline prices respond more immediately to increases than decreases in crude oil prices in the international market. The long-run relationship between crude oil prices and petroleum products using advanced estimation techniques has also been confirmed in subsequent studies (Asche et al. 2006, Villar and Joutz 2006). Lahiani et al. (2017) demonstrate that oil price is still a significant 'predictor' of petroleum products prices in the short run. Using Quantile Autoregressive Distributed Lags (QARDL), Lahiani et al. (2017) find that energy prices are cointegrated with crude oil prices. These findings confirm that energy prices are simultaneously adjusted following changes in crude oil prices. Gorton et al. (2012) examine the relationship between petroleum product futures' excess returns and inventories. Their results show that cross-sectional and time-series variation of the risk premium has an inverse relationship with the level of inventory of gasoline, heating oil and crude oil prices.

Similarly, using daily and weekly data on crude oil, heating oil, and gasoline for the period 1984–2001, Pindyck (2004) argue that speculation in the oil market may partially explain the volatility and dynamic causal relationship between crude oil and petroleum products. Hammoudeh et al. (2003) examine prices of oil and petroleum products for five commodity centres inside and outside the United States. Using a GARCH model, Hammoudeh et al. (2003) report significant evidence of spillover effects in crude oil, heating oil and gasoline markets, in terms of spot and futures contract prices. Similarly, introducing speculation related variables into univariate GARCH-type models of energy futures price volatility, Manera et al. (2016) examine how speculation increases or decreases energy futures price volatility. The estimated GARCH models for crude oil, heating oil, gasoline, and natural gas, and they found that higher speculation is associated with lower volatility. Their empirical findings suggest that speculation help the market participants in decreasing their volatility.

Discussing the causes of asymmetric association between crude oil prices and refined petroleum products, Kaufmann and Laskwski (2005, p. 1595) conclude that: '*asymmetries in motor gasoline prices probably are caused by competitive stock and production behaviors, which clearly do not warrant a policy response'*. The relationship between crude oil and refined petroleum products has been empirically established in the context of major economies, including the UK (Bacon 1991), USA (Borenstein et al. 1997), Italy, France, Spain and Germany (Galeotti et al. 2002). Based on prior empirical work, it can be argued that oil prices are used as a benchmark in assessing other natural resources, risk assessment strategies.

3.0 Methodology

3.1. Wavelet multiple correlation and cross-correlation procedure

Several researchers (Tiwari et al. (2013); Andrieş et al. (2016); Das et al. (2018); Jena et al. (2018)) used the Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross-Correlation (WMCC) methods used as an extent of market integration. Likewise, to measure the degree of integration in the crude oil and petroleum products, we used Wavelet multiple correlations and cross-correlation procedure. These methods were first introduced by Fernández-Macho (2012) because of certain limitations of pairwise correlations and cross-correlations. Following Fernandez Macho (2012), let $X_t = \{x_{1t}, x_{2t}, \ldots, x_{nt}\}$ be a multivariate stochastic model and let $W_t^j = \{w_{1t}^j, w_{2t}^j, \ldots, w_{nt}^j\}$ be the respective scale λ_j wavelet coefficients. The wavelet coefficients were $w_{it}^j, i = 1, \ldots n$ resulting from the application of the maximum overlap discrete wavelet transform (MODWT) to each data generating process $x_{it}, i = 1, \ldots n$. The wavelet multiple correlations (WMC) denoted hereby $\varphi_X(\lambda_j)$ and introduced by Fernandez Macho (2012) as a single set of multiscale correlation is computed from X_t via a subsequent procedure. However, at each wavelet scale λ_j, the square root of regression coefficient of determination is computed in that linear combination of components $w_{it}^j, i = 1, \ldots n$ by that such coefficient of determination attains its maximum[1]. The coefficient of determination related to

[1]For more details about the procedure, we refer the reader to Fernandez Macho (2012).

the regression of a variable z_i on a set of regressors $\{z_i, k \neq i\}$ is acquired as $R^2 = 1 - 1/\rho^{ii}$ where ρ^{ii} is the ith diagonal element of the inverse of the correlation matrix P. The WMC is given by the following formula:

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{max \operatorname{diag} P_j^{-1}}} \qquad (1)$$

Where P_j denotes the $(n \times n)$ correlation matrix of the process W_t^j and the operator max diag(▪) selects the optimal element in the diagonal of the argument. On the repose of the variable, the regression of z_i could be articulated as to be equivalent to the correlation square of the R^2 coefficient. It is equal to the correlation square between observed values of z_i and fitted values $\hat{z}_i$ gained from the regression process. Under certain conditions, the WMC can be specified as follows:

$$\varphi_X(\lambda_j) = \operatorname{corr}\left(w_{it}^j, \hat{w}_{it}^j\right) = \frac{\operatorname{cov}\left(w_{it}^j, \hat{w}_{it}^j\right)}{\sigma_{w_{it}^j}\sigma_{\hat{w}_{it}^j}}, i = 1, \dots n \qquad (2)$$

In the above equation, the wavelet variances and co-variances are provided by:

$$Var(W_{ijt}) = \delta_j^{-2} = \frac{1}{T_j} \sum_{t=:j-1}^{T-1} W_{ijt}^2$$

$$Var(\widehat{W}_{ijt}) = \delta_j^{-2} = \frac{1}{T_j} \sum_{t=:j-1}^{T-1} \widehat{W}_{ijt}^2$$

$$Var(W_{ijt}, \widehat{W}_{ijt}) = \delta_j^{-2} = \frac{1}{T_j} \sum_{t=:j-1}^{T-1} W_{ijt}^2 , \widehat{W}_{ijt}^2$$

Where w_{it}^j is selected to maximize the coefficient of determination R_i^2 that corresponds to the regression of the dependent variable z_i on a set of regressors $\{z_l, l \neq i\}$. The coefficients $\hat{w}_{it}^j$ denote the fitted values in the regression of w_{it}^j on the rest of wavelet coefficients across the scale λ_j. $\sigma_{w_{it}^j}^2$ and $\sigma_{\hat{w}_{it}^j}^2$ represent the wavelet variances of w_{it}^j and $\hat{w}_{it}^j$, respectively. $\operatorname{cov}\left(w_{it}^j, \hat{w}_{it}^j\right)$ designates the wavelet covariance between w_{it}^j and $\hat{w}_{it}^j$.

As mentioned in Fernandez Macho (2012), the wavelet multiple cross-correlation can be deduced from the specification of the WMC by simply inserting a lag term h, in-between the observed and fitted values for the selected criterion component. The following consistent estimate specifies the WMCC:

$$\tilde{\varphi}_X\left(\lambda_j\right)=\operatorname{corr}\left(\tilde{w}_{it}^j,\hat{\tilde{w}}_{i,t+h}^j\right)=\frac{\operatorname{cov}\left(\tilde{w}_{it}^j,\hat{\tilde{w}}_{i,t+h}^j\right)}{\sigma_{\tilde{w}_{it}^j}\sigma_{\hat{\tilde{w}}_{i,t+h}^j}},\, i=1,\ldots n \tag{3}$$

Fernandez Macho (2012) constructed a significant confidence interval for the WMC as below:

$$CI_{1-\alpha}\left(\varphi_X(\lambda_j)\right)=\tanh\left[\tilde{z}_j\pm\phi_{1-\frac{\alpha}{2}}^{-1}\sqrt{\frac{T}{2^j}-3}\right] \tag{4}$$

3.2 DY time-domain spillover method

After analysing the Wavelet multiple correlation and cross-correlation, we then employ the methodology of Diebold and Yilmaz (2012). The DY method develops a spillover index as well as additional spillover measures for various inflation indices of four Euro-area economies. The DY spillover index is based on a vector autoregressive (VAR) model. It computes the forecast error variance decompositions using a generalized vector autoregression (FEVD). In implementing DY methodology, we start our procedures by estimating an estimate of VAR(*p*) process and its FEVD. Let us describe the *n*-variate process $x_t=\left(x_{t,1},\ldots,x_{t,n}\right)$ by the structural VAR(*p*) at $t=1,\ldots,T$ as following:

$$\Phi(L)x_t=\varepsilon_t, \tag{5}$$

where $\Phi(L)=\sum_h \Phi_h L^h$ is $n\times n$ *p*-th order lag-polynomial and ε_t is a white-noise with non-diagonal covariance matrix Σ. Assuming that the roots of $|\Phi(z)|$ lie outside the unit circle, the VAR process has the following moving average $\mathrm{MA}(\infty)$ representation:

$$x_t=\Psi(L)\varepsilon_t, \tag{6}$$

Where $\Psi(L)$ is an $n\times n$ infinite lag polynomial matrix of coefficients. Following Diebold and Yilmaz (2012), generalised FEVD can be written as follows:

$$\left(\theta_H\right)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left(\left(\Psi_h\Sigma\right)_{j,k}\right)^2}{\sum_{h=0}^{H}\left(\Psi_h\Sigma\Psi_h'\right)_{j,j}}, \tag{7}$$

Where Ψ_h is a $n \times n$ matrix of coefficients corresponding to lag *h*, and $\sigma_{kk} = (\Sigma)_{k,k}$. The $\left(\theta_H\right)_{j,k}$ denotes the contribution of the *k*-th variable of the system to the variance of forecast error of the element *j*. In the generalised VAR framework, the shocks to each variable are not orthogonalised, and thus the sum of each row of $\left(\theta_H\right)_{j,k}$ does not generally equal to one. Therefore, each element of the decomposition matrix can be normalised by dividing with the row sum, i.e.:

$$\left(\tilde{\theta}_H\right)_{j,k} = \frac{\left(\theta_H\right)_{j,k}}{\sum_{k=1}^{n}\left(\theta_H\right)_{j,k}}, \text{ with } \sum_{k=1}^{n}\left(\tilde{\theta}_H\right)_{j,k} = 1 \text{ and } \sum_{j,k=1}^{n}\left(\tilde{\theta}_H\right)_{j,k} = N. \tag{8}$$

The connectedness measure is then defined as the share of variances in the forecasts contributed by other than own errors, or equally as the ratio of the sum of the off-diagonal elements to the sum of the whole matrix (DieboldandYilmaz2012):

$$C_H = 100 \times \frac{\sum_{j \neq k}\left(\tilde{\theta}_H\right)_{j,k}}{\sum\left(\tilde{\theta}_H\right)_{j,k}} = 100\left(1 - \frac{Tr\left\{\tilde{\theta}_H\right\}}{\sum\left(\tilde{\theta}_H\right)_{j,k}}\right), \tag{9}$$

Where $Tr\{\cdot\}$ is the trace operator. As a result, the connectedness is the relative contribution to the forecast variances from the other variables in the system. C_H measures the connectedness of the whole system. Further, we also estimate the directional spillovers received by market j from all the different markets k in our sample and vice-versa. The net volatility spillovers from each market to all other markets is the difference between directional spillover received from the markets to directions spillovers to the market.

3.3 BK frequency-domain spillover method

Now, we discuss the method for measuring connectedness in frequency domain following Barunik and Krehlik (2018). As seen in equation-1, the connectedness measure is based on an impulse function Ψ_h defined in the time-domain. Let us consider a frequency response function $\Psi\left(e^{-iw}\right) = \sum_h e^{-iwh}\,\Psi_h$, which can be obtained from the Fourier transform of the coefficients Ψ, with $i = \sqrt{-1}$. The generalised causation spectrum over frequencies $\omega = \in (-\pi, \pi)$ is specified as:

$$\left(f(\omega)\right)_{j,k} \equiv \frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-iw}\right)\Sigma\right)_{j,k}\right|^2}{\left(\Psi\left(e^{-iw}\right)\Sigma\,\Psi'\left(e^{+iw}\right)\right)_{j,j}}, \tag{10}$$

Where $\Psi\left(e^{-iw}\right)$ is the Fourier transform of the impulse response Ψ as defined above. $\left(f(\omega)\right)_{j,k}$ represents the portion of the spectrum of j-th variable at frequency ω due to shocks in k-th variable. Thus, we can interpret the quantity as a within frequency causation, as denominator holds a spectrum of the j-th variable, i.e. on-diagonal element of the cross-spectral density of x_t, at given frequency ω. To obtain a natural decomposition of the original generalised FEVD to frequencies, we can simply weight the $\left(f(\omega)\right)_{j,k}$ by the frequency share of variance of the j variable. We define the weighting function as:

$$\Gamma_j(\omega) = \frac{\left(\psi\left(e^{-iw}\right)\Sigma\,\psi'\left(e^{+iw}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-i\lambda}\right)\Sigma\,\Psi'\left(e^{+i\lambda}\right)\right)_{j,j} d\lambda}, \tag{11}$$

Where the power of j-th variable at a given frequency, which sums through frequencies to a constant value of 2π. While the Fourier transform of the impulse response is, in general, a complex-valued quantity, the generalised causation spectrum is the squared modulus of the weighted complex numbers, hence producing a real quantity. We will then have a frequency band $d = (a,b) : a, b \in (-\pi, \pi), a < b$. Consequently, the generalised FEVD on some frequency banded can be defined as:

$$\left(\theta_d\right)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)\left(f(\omega)\right)_{j,k} d\omega. \tag{12}$$

Applying the spectral representation of generalised FEVD, connectedness can be reported for a particular frequency band. We can define the scaled generalised FEVD on the frequency banded as:

$$\left(\tilde{\theta}_d\right)_{j,k} = \frac{\left(\theta_d\right)_{j,k}}{\sum_k \left(\theta_\infty\right)_{j,k}}. \tag{13}$$

The frequency connectedness on the frequency band, i.e. band *d* is defined as:

$$C_d^F = 100\left(\frac{\sum_{j\neq k}\left(\tilde{\theta}_d\right)_{j,k}}{\sum\left(\tilde{\theta}_\infty\right)_{j,k}} - \frac{Tr\left\{\tilde{\theta}_d\right\}}{\sum\left(\tilde{\theta}_\infty\right)_{j,k}}\right) \tag{14}$$

Finally, the frequency band *d* overall connectedness within can be presented as:

$$C_d^W = 100\left(1 - \frac{Tr\left\{\tilde{\theta}_d\right\}}{\sum\left(\tilde{\theta}_d\right)_{j,k}}\right). \tag{15}$$

Within connectedness, it reports the connectedness effect that can be observed within the frequency band and is weighted by the power of the series on the given frequency band exclusively. Conversely, the frequency connectedness further decomposes the original connectedness in several parts, and sum produces the original connectedness measure.

4. Data and Empirical analysis

4.1. Data

We used daily data of crude oil prices and petroleum products for the period 2003/01/11 – 2018/03/12. The details about the petroleum products are provided in Appendix A1. We used West Texas Intermediate (WTI) as a proxy of oil prices, and all the data used in the paper is sourced from the International Energy Agency (IEA). Table-1 exhibits the descriptive statistics of all the variables, which shows that all the series have positive arithmetic mean. The highest mean is for Brent, whereas propane with the lowest one. Based on the statistics of the standard deviation, we conclude that RBOB. Gasoline the most volatile series, whereas the lowest one is with diesel.

[Insert Table 1 about here]

The skewness coefficients are positive for the majority of the series with an exemption of the diesel, propane, and gasoline series. The kurtosis coefficients are above three for all the series, which is the value for the Gaussian distributions. These findings show that the probability distributions of all return series are skewed and leptokurtic. Further, Jarque-Bera statistics also rejects the normal distribution. Additionally, we also display the results for Dickey and Fuller (1979), Phillips and Perron (1988), as well as the KPSS test for unit root testing. The results for all three tests specify that all return series are stationary.

We also present the graphs of the raw data for all the nine series Appendix B in Figure-B1. It is clear from the graph that all the series have a big dip during the financial crisis of 2008-2009. The oil prices dropped from $147 in July 2008 to $33 in February 2009, whereas the gas prices fell from $14 to $4. Throughout the time of our analysis, the price of oil and petroleum products fluctuate very much. It is further confirmed from Figure-B2 (see Appendix B), which display the time-series graph of log-return data. A quick look at Figure-B1 (Appendix B) shows that the overall return series of oil and petroleum products share common spikes over the sample period. We can see that the majority of the series are more volatile during the financial crisis of 2008-09. Further, the log-return series are also volatile at the end of our sample period.

In Figure-1, we plot the normal distribution and the pairwise correlation of the series for the data used. The null hypothesis of the normal distribution is rejected for all the series. It confirms our initial finding using the Jarque-Bera test. We find that the majority of the series has a very high correlation among their pairs (more than 0.90 in the majority of cases). These findings are also consistent with the initial finding (see Figure-B1 and B2 in Appendix B), where the series often move together.

[Insert Figure 1 about here]

The correlation analysis of log-returns series based on a clustering algorithm is presented in Figure-2. Blue line plots are presented by positive correlation among the series. The distance among the points is calculated based on the absolute value of correlation. The shorter the distance, the thicker the width and transparency of the cluster. Majority of the series establishes a high degree of clustering. We only find, propane is considered to have a weaker rate clustering as well as distantly clustered with other series.

[Insert Figure 2 about here]

Also, we show the network analysis of correlations among log-returns series in Figure-3. Figure-3 presents three types of correlation network analysis, i.e. Pearson Correlation Network, Spearman Correlation Network, and Kendall Correlation Network. We find similar results from all three correlation analysis as in the majority of the cases. The correlation is higher, i.e. more significant than 0.65.

[Insert Figure 3 about here]

We also examined the network analysis. More specifically, we used the two well know types of the network analysis, i.e. partial contemporaneous correlations (contemporaneous network) and partial directed correlations (temporal). The partial directed correlation reports the results of the direction of connectedness. We present the graphs of these two analyses in Figure-4. This figure demonstrates that there is a high degree of partial contemporaneous correlation between J.F, H.O, USG, Ds and NYH, USG. Whereas for the partial directed correlations, we find that there is a direct strong directional correlation from USG to J.F and USG to NYH.

[Insert Figure 4 about here]

4.2. Co-movement of crude oil and petroleum products

We present results from the Wavelet multiple correlation and cross-correlation between crude oil and petroleum products in Figure-5, 6, and 7. Figure-5 shows the Wavelet multiple correlations between crude oil and petroleum products for the period of 2003/01/11 to 2018/03/12. The blue lines in the graph represent Lower (L) limits and Upper (U) respectively at a 95% confidence interval. We can see that the multiple correlations are relatively high at almost every time scale. The highest relationship between crude oil and petroleum products within a week time scale is 0.85 for heating oil. This consistency continues to increase to 0.93 at quarterly scale. However, the multiple correlations rose from 0.94 to 0.99 for gasoline over more extended time scale, i.e., between semi-annual to annual, and longer period. It confirms the linear relationship among crude oil and heating oil at a short time scale, whereas with gasoline at medium and long time scale.

[Insert Figure 5 about here]

The results from the wavelet multiple cross-correlations for crude oil and petroleum products are presented in Figure-6. It is observed that heating oil work as a leader or follower for a majority of the period. More specifically, heating oil leads from within a week to quarterly scale. However, for a more extended period, i.e., semi-annual and annual scale gasoline work as a potential leader.

[Insert Figure 6 about here]

Figure-7 presents the results for wavelet multiple cross-correlations for multiple time scales with leads and lags up to a month trading period. In the figure, every wavelet scale plot displays at its upper-right corner the variable that maximizes the multiple correlations against a linear combination of the rest of variables. Therefore, this signals a possible follower or leader for the entire system. The lower and upper bounds are denoted with redlines at a 95% confidence interval. The results are almost the same as we found in the prior results (i.e., Figure-6 and 7). Heating oil leads the market up to level 5 at almost all the lead and lags. However, this was overtaken by gasoline over level 6 to level 8. Furthermore, we also find an asymmetric behavior at a majority of the lags and frequency levels.

[Insert Figure 7 about here]

4.3. Return and volatility spillovers across crude oil and petroleum products (DY)

We also investigate the spillover effect of oil prices on petroleum products. The result of the DY model is presented in Table-2. In Table-2, row contribution "To" indicates the spillover impact directed by one series of crude oil or petroleum products to all other series. Whereas, the last column of Table-2, "From," represents the total spillovers received by crude oil or petroleum products from all other series. The last row of Table-2, i.e. "Net" exhibits the total of the net-pair-wise directional spillovers, where a positive (negative) value indicates a net-transmitter (net-recipient).

The lower right corner of Table-2 shows that the total spillover reaches 62.29%, indicating a high level of volatility spillover between WTI and other petroleum products. Next to examining the directional spillovers transmitted 'To', heating oil is the highest contributor to other products, contributing 93.87%, followed by Jet Fuel (80.19%), and NYH. Gasoline (78.39%). For an investor, these findings imply that heating oil is the key source of volatility spillover shock to others, and they should observe their portfolio of investment. The most interesting results are for Brent as it contributes only total 0.72% of volatility spillover to other markets, and it receives 4.05% of volatility spillover from its counterpart market. Moving forward, the net spillovers ('To'–'From'), six of the series contribute with as a transmitter and heating oil is the largest net transmitter of spillovers, with a net contribution of 17.79%, followed by the Jet. Fuel (6.56%). Whereas three of the series Propane, ROBOB. Gasoline and Brent are net recipients of spillovers with net values -20.81%, -18.65%, and -3.33%, respectively. We also estimated the directional volatility spillovers from all the oil products to a particular product. These spillovers range between 4.05 (Brent) to 76.14 (heating oil).

[Insert Table 2 about here]

Furthermore, the returns of the Brent show the least value of the volatility transmission in the petroleum products. The highest spillovers are reported from diesel to heating oil and Jet fuel to heating oil with volatility transmitted of 139.95% and 139.23%, respectively. Figure-8 displays the total spillover across all the series in the data using DY model. While Figures 9 and 10 exhibits the total spillover to and from other markets, respectively. Lastly, Figure 11 presents the net spillover among all the series. From these graphs, we can conclude that the series vary over time more specifically for the overall spillover shows higher values between 2008 to 2014 and then gradually drop down and remain lower after 2014.

4.4. Return and volatility spillovers across crude oil and petroleum products (DY)

The main purpose of this section is to provide more detail related to the direction and magnitude of volatility spillover. For this purpose, we break down the connectedness into five different frequency bands for the spillover index, i.e. 1-2 days (Freq1), 2-4 days (Freq2), 4-8 days (Freq3), 8-16 days (Freq4), and 16 days to infinity (Freq5). These bands are computed as d_1[3.14, 1.57], d_2[1.57, 0.79], d_3[0.79, 0.39], d_4[0.39, 0.20], and d_5[0.20, 0.00], respectively. In Table-3, the term "TO_ABS" estimates the spillovers from a given series to all other series, and, term "TO_WTH" also estimates the spillovers from a given series to all other series as well as spillover from its own innovation. Likewise, the terms in last two columns of Table-3 "From_ABS" and "From_WTH" denotes spillovers from all other series to a given series along with spillovers received by a series from all other series, including own innovations respectively. These results in line with the earlier finding of Lahiani et al. (2017), who confirm that oil price, can predict the petroleum product prices.

[Insert Figure 8, 9, 10, 11 about here]

The results from the Barunik and Krehlik (2018) are presented in Table-3. From the table, we conclude that overall spillover index ranges between 60.50% and 65.50%. Furthermore, the directional spillover transmitted 'TO_ABS' the highest spillover across all frequency bands is for Heating Oil. These findings suggest that Heating Oil is the most significant contributor to spillover effects to other series. On the contrary, Brent is the least contributor to its counterpart across all frequency bands, and this spillover effect becomes more week for more extended frequencies. Our findings are consist with the findings of Hammoudeh et al. (2003) find evidence of spillover effects in crude oil, heating oil as well as gasoline markets. A number of researcher find a significant relationship among crude oil and refined petroleum products established in the setting of major economies such as the United Kingdom (Bacon 1991), United State of America (Borenstein et al. 1997), France, Germany, Italy, and Spain (Galeotti et al. 2002)

Looking at both net transmitter of spillover, i.e., "TO_ABS" and "FROM_ABS" the least transmitter is for the Brent, whereas the highest net transmitter varies from petroleum products at a different frequency. For example, at Freq. 1 Heating Oil transmitter is the highest one and at Freq. 5 Diesel with the highest transmitter. At the next step, we also present the estimations within connectedness of WTI and petroleum products, i.e., TO_WTH. Heating oil is the most significant contribution to products with a contribution of 95.49%, 94.59%, 92.43%, and 85.23% for frequencies 1 to 5 respectively.

[Insert Table 3 about here]

We also present the time-series graph of the overall directional connectedness in Figure-12. From the graphs, we conclude that the strength of spillovers varies at different times as well as different time frequencies. A significant rise in the overall spillover is recorded during the global financial and European debt crisis. More details about "To" and "From" spillover is presented in figures in the Appendix D. Overall we conclude in all cases, the spillover is time-varying and reacts significantly to the economic and oil events.

[Insert Figure 12 about here]

5. Conclusion and Policy Implications

We analysed the relationship between crude oil and petroleum products' prices for the period of 2003/01/11 to 2018/03/12. We used a range of methods starting with network analysis of correlations, which conclude that there is a high level of partial contemporaneous relationship between jet fuel, heating oil, US gasoline as well as diesel. As a second measure of analysis, the results from partial direct correlation conclude strong directional correlation from US gasoline to Jet fuel and US gasoline to NHY gasoline. To further analyse this relationship, we estimated the Wavelet multiple correlation and cross-correlation between crude oil and petroleum products. The results support our initial findings. We determined that heating oil act as a leader for a short time horizon, whereas gasoline at medium and longer time scale.

Lastly, we test the relationship between crude oil and oil products using formal models, i.e., Diebold and Yilmaz (2012) and Barunik and Krehlik (2018). The DY results also establish a high level of volatility spillover among WTI and petroleum products, and heating oil has the highest contributor to others. Similar findings confirmed using the BK model. The highest spillover across all the frequency bands is for heating oil. However, we find interesting results for Brent, which contribute least to its counterpart at all frequency bands.

As our study covers several energy-related events and shocks, we expect our research has implications for a wide range of market participants, including investors, hedge funds, speculators, as well as for energy policy, with different temporal horizons. Our proposed methodological framework can be enormously useful in applying it for hedging purpose in the energy market. Finally, this research has practical implications for petroleum products trade and transport. This paper assists ship owners', traders' and charterers' in their strategic financial decision-making and financial forecasting process. For petroleum products, we argue that the asymmetries may be potentially caused by the contractual arrangements between retailers and consumers in the energy markets. As a result, these arrangements might be beneficial for consumers because they may be intending to pay additional costs related to the asymmetric price in the oil-petroleum market. Finally, contrary to the efficient market hypothesis (EMH), investors can use our findings and methodological approach in predicting the prices and implied volatility of energy prices.

We suggest several avenues for future research. First, future studies may also consider the relationship between spot and futures prices of crude oil in an international comparative context. Second, future studies may also examine the role of speculation in determining the causal relationship between oil and petroleum products. Our study did not consider a number of external exogenous factors, such as inventory levels, storage costs, implied volatility, and price discovery in the petroleum markets. Doing so was beyond the scope of this research and is therefore left out for future research.

AVAILIBITY OF DATA

Data available in article supplementary material.

The data that supports the findings of this study are available in the supplementary material of this article.

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Table-1: Descriptive Statistics

Note: This table presents the descriptive statistics of all the series used in the analysis. For unit root and stationarity tests, lag-selection is based on SIC. *** denotes rejection of the null hypothesis of unit root at 1% level of significance.

	WTI	Brent	Heating. Oil	Diesel.	Jet. Fuel	Propane	RBOB. Gasoline	NYH. Gasoline	USGC. Gasoline
Observations	3762	3762	3762	3762	3762	3762	3762	3762	3762
Minimum	-0.1519	-0.1683	-0.1271	-0.1843	-0.2775	-0.3979	-0.1933	-0.2533	-0.3868
Quartile 1	-0.0126	-0.011	-0.012	-0.0113	-0.0121	-0.0101	-0.0163	-0.0139	-0.015
Median	0.0007	0.0003	0	0	0	0	0	0.0009	0
Arithmetic Mean	0.0001	0.0002	0.0001	0.0001	0.0001	0	0.0001	0.0001	0.0001
Geometric Mean	-0.0002	0	-0.0001	-0.0001	-0.0002	-0.0003	-0.0005	-0.0002	-0.0003
Quartile 3	0.0128	0.0118	0.0125	0.0115	0.0126	0.0112	0.0159	0.0145	0.0156
Maximum	0.1641	0.1813	0.1486	0.1233	0.3264	0.1998	0.4838	0.2351	0.3717
SE Mean	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0006	0.0004	0.0005
LCL Mean (0.95)	-0.0006	-0.0005	-0.0006	-0.0006	-0.0007	-0.0007	-0.001	-0.0007	-0.0008
UCL Mean (0.95)	0.0009	0.0009	0.0008	0.0008	0.0009	0.0008	0.0012	0.001	0.0011
Variance	0.0006	0.0005	0.0005	0.0005	0.0006	0.0006	0.0012	0.0007	0.0009
Std.Dev.	0.0241	0.0217	0.0224	0.0216	0.0251	0.0245	0.0347	0.027	0.0302
Skewness	0.0034	0.1003	0.038	-0.179	0.0914	-1.3056	0.907	-0.0324	0.143
Kurtosis	4.4685	4.5848	3.0259	3.9387	16.0075	24.4888	14.4747	8.0766	20.1116
Jarque-Bera	3129.951	3301.178	1436.13	2451.778	40170.62	95071.57	33357.69	10225.57	63414.28
Unit root and stationarity tests									
ADF test with constant	-63.704***	-60.548***	-64.771***	-61.295***	-45.773***	-39.986***	-60.349***	-61.804***	-60.802***
PP Test with constant	-63.701***	-60.566***	-64.741***	-61.389***	-61.691***	-58.022***	-60.349***	-61.835***	-60.875***
KPSS test with constant	0.1169	0.1413	0.118	0.112	0.1222	0.0849	0.0267	0.086	0.0718

Table-2: Returns Spillover (DY 2012)

Note: This table present the result of the DY model. The row contribution "To" indicate the spillover impact directed by one series of crude oil or petroleum products to all other series. Whereas, the last column of table "From," represents the total spillovers received by crude oil or petroleum products from all other series. The last row of the table "Net" exhibits the total of the net-pair-wise directional spillovers, where a positive (negative) value indicates a net-transmitter (net-recipient).

	WTI	Brent	Heating. Oil	Diesel.	Jet. Fuel	Propane	RBOB. Gasoline	NYH. Gasoline	USGC. Gasoline	F
WTI	252.81	1.35	136.8	109.89	105.39	67.32	44.64	93.96	87.84	
Brent	5.94	863.19	5.22	4.59	4.14	1.98	2.52	6.66	5.76	
Heating.Oil	118.17	0.45	214.92	139.95	139.23	54.27	48.06	98.64	86.31	
Diesel.	105.93	0.45	156.33	239.94	124.56	49.77	55.98	88.74	78.3	
Jet.Fuel	100.35	0.63	154.08	122.76	237.6	43.74	43.2	94.59	103.05	
Propane	103.23	0.9	97.56	80.91	72.54	381.78	33.12	69.03	61.02	
RBOB.Gasoline	66.69	1.71	80.46	83.97	66.06	30.87	364.95	103.59	101.7	
NYH.Gasoline	93.24	0.63	113.04	90.81	98.01	43.2	69.3	245.07	146.61	
USGC.Gasoline	89.01	0.72	101.7	82.17	111.42	39.78	70.38	150.21	254.52	
Contribution to others	75.87	0.72	93.87	79.47	80.19	36.81	40.77	78.39	74.52	5
Contribution including own	935.37	870.03	1060.11	954.99	958.95	712.71	732.15	950.49	925.11	
Net Spillover (to others - from others)	3.914874	-3.33894	17.79487	6.116214	6.556839	-20.8058	-18.6486	5.612711	2.797894	

Table-3: Returns Spillover (BK 2018)

Note: This table presents the results of the connectedness based on five different frequency bands for the spillover index i.e. 1-2 days ($Freq_1$), 2-4 days ($Freq_2$), 4-8 days ($Freq_3$), 8-16 days ($Freq_4$), and 16 days to infinity ($Freq_5$). These bands are computed as d_1[3.14, 1.57], d_2[1.57, 0.79], d_3[0.79, 0.39], d_4[0.39, 0.20], and d_5[0.20, 0.00], respectively. In table, the term "TO_ABS" estimates the spillovers from a given series to all other series, and, term "TO_WTH" also estimates the spillovers from a given series to all other series as well as spillover from its own innovation.

$Freq_1$: The spillover table for band: 3.14 to 1.57 roughly corresponds to 1 days to 2 days.

	WTI	Brent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
WTI	141.48	0.54	75.06	60.12	56.79	37.17	25.02	51.84	50.94	39.69	76.95
Brent	3.24	445.05	1.8	1.62	2.34	0.72	0.72	2.97	2.52	1.71	3.42
Heating. Oil	66.87	0.18	120.78	76.23	73.71	28.8	27.9	54.18	48.78	41.85	81
Diesel.	55.89	0.09	80.82	124.83	61.29	23.85	28.35	45	41.58	37.44	72.45
Jet. Fuel	55.71	0.36	82.08	65.16	124.02	22.68	22.68	48.6	49.5	38.52	74.61
Propane	49.77	0.63	42.12	33.39	28.89	182.61	11.79	27.81	26.1	24.48	47.43
RBOB.Gasoline	35.28	0.72	44.73	46.35	35.19	15.03	185.22	51.48	44.82	30.42	58.86
NYH.Gasoline	53.19	0.36	62.37	50.04	51.03	23.04	37.44	126.27	68.22	38.43	74.34
USGC.Gasoline	50.13	0.45	54.99	43.92	53.46	20.43	36.09	72.18	128.25	36.9	71.37
TO_ABS	41.13	0.36	49.32	41.85	40.32	19.08	21.15	39.33	36.9	**32.16**	
TO_WTH	79.56	0.72	95.49	81.09	78.03	36.9	40.86	76.14	71.46		**62.27**
Net Spillover (to others - from others)	1.381	-1.383	7.4836	4.433	1.779	-5.408	-9.27666	0.940711	0.050293		

$Freq_2$: The spillover table for band: 1.57 to 0.79 roughly corresponds to 2 days to 4 days.

	WTI	Brent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
WTI	52.83	0.27	30.15	24.93	27.63	15.03	8.01	19.62	18.54	16.02	69.57
Brent	0.45	197.1	1.71	1.62	0.72	0.18	0.27	1.44	0.99	0.81	3.51
Heating.Oil	22.59	0.09	47.52	30.33	34.11	10.71	8.1	20.97	17.28	16.02	69.57
Diesel.	21.24	0.09	36	55.35	31.86	10.62	10.17	19.35	15.12	16.02	69.66
Jet.Fuel	20.52	0.09	35.82	27.27	62.19	8.55	8.28	22.77	25.74	16.56	71.82

	WTI	rent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
Propane	24.3	0	25.56	20.7	22.41	87.75	7.56	18.45	15.93	15.03	65.07
RBOB.Gasoline	13.32	0.45	17.19	17.73	17.37	6.66	82.98	25.47	27.18	13.95	60.39
NYH.Gasoline	17.73	0.18	25.65	20.16	25.56	9.54	13.14	62.19	34.83	16.29	70.74
USGC.Gasoline	18.45	0.18	24.21	19.44	33.3	9.81	13.95	40.95	62.01	17.82	77.31
TO_ABS	15.39	0.18	21.78	18	21.42	7.92	7.74	18.81	17.28	**14.28**	
TO_WTH	66.87	0.63	94.59	78.21	93.06	34.29	33.48	81.54	75.06		**61.96**
Net Spillover (to others - from others)	-0.6183	-0.66448	5.777452	1.974777	4.881443	-7.09621	-6.2044	2.475665	-0.52595	0	0

Freq3: The spillover table for band: 0.79 to 0.39 roughly corresponds to 4 days to 8 days.

	WTI	rent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
WTI	30.24	0.18	16.47	12.33	9.99	7.29	5.49	11.25	9	8.01	67.5
Brent	1.17	106.38	1.35	1.17	0.9	0.18	0.27	0.54	1.44	0.81	6.66
Heating.Oil	11.34	0	22.23	14.67	14.04	6.39	5.13	11.16	9.27	8.01	67.59
Diesel.	11.61	0	18.99	26.37	14.13	6.75	7.11	11.88	9.81	8.91	75.51
Jet.Fuel	9.63	0	17.73	13.23	25.56	5.31	4.77	10.89	12.69	8.28	69.75
Propane	11.88	0.09	12.87	12.42	8.64	54.81	5.85	10.17	8.28	7.83	65.79
RBOB.Gasoline	5.49	0.36	7.74	7.56	6.21	2.97	47.88	10.8	12.87	6.03	50.67
NYH.Gasoline	9.9	0	12.51	9.36	10.35	5.04	8.01	29.79	22.05	8.55	72.54
USGC.Gasoline	8.64	0	10.8	8.28	13.14	4.23	9.54	18.36	35.46	8.1	68.58
TO_ABS	7.74	0.09	10.98	8.73	8.64	4.23	5.13	9.45	9.54	**7.16**	
TO_WTH	65.43	0.72	92.43	74.07	72.72	35.82	43.29	79.83	80.28		**60.5**
Net Spillover (to others - from others)	-0.24894	-0.70351	2.94815	-0.16429	0.344973	-3.55181	-0.87296	0.864475	1.383912		

Freq4: The spillover table for band: 0.39 to 0.20 roughly corresponds to 8 days to 16 days.

	WTI	rent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
WTI	14.58	0.18	7.38	5.49	4.86	3.33	2.61	5.31	4.32	3.69	59.4
Brent	0.63	55.53	0.27	0.18	0.18	0.27	0.45	0.63	0.36	0.36	5.22
Heating.Oil	8.1	0.09	11.61	8.28	7.56	3.51	2.88	5.94	5.04	4.59	73.26
Diesel.	8.01	0.09	9.72	14.85	7.47	3.69	4.23	5.85	5.4	4.95	78.84
Jet.Fuel	6.84	0.09	9.09	7.56	12.15	3.15	3.06	5.85	7.02	4.77	75.51
Propane	7.74	0.09	7.47	6.03	5.04	25.92	3.24	5.58	4.59	4.41	70.56
RBOB.Gasoline	5.76	0.18	5.04	4.95	3.15	2.7	23.49	7.29	7.74	4.05	65.25
NYH.Gasoline	6.21	0	6.39	5.13	5.31	2.52	4.68	13.59	10.89	4.59	73.08
USGC.Gasoline	5.76	0	5.76	4.77	5.49	2.43	4.86	9.27	14.94	4.23	68.13
TO_ABS	5.49	0.09	5.67	4.68	4.32	2.43	2.88	5.13	5.04	**3.97**	
TO_WTH	87.12	1.26	90.72	75.15	69.21	38.25	45.99	81.18	80.28		**63.25**
Net Spillover (to others - from others)	1.74243	-0.24989	1.093806	-0.23009	-0.39728	-2.02383	-1.20438	0.505522	0.763707		

Freq5: The spillover table for band: 0.20 to 0.00 roughly corresponds to 16 days to Inf. days.

	WTI	rent	Heating.Oil	Diesel.	Jet.Fuel	Propane	RBOB.Gasoline	NYH.Gasoline	USGC.Gasoline	FROM_ABS	FROM_WTH
WTI	13.68	0.18	7.65	7.02	6.12	4.41	3.6	5.85	5.04	4.41	61.56
Brent	0.45	58.95	0.09	0	0.09	0.54	0.9	1.17	0.54	0.45	5.67
Heating.Oil	9.18	0.09	12.78	10.44	9.63	4.86	4.05	6.48	5.85	5.67	78.39
Diesel.	9.09	0.18	10.71	18.45	9.81	4.86	6.12	6.57	6.48	5.94	83.16
Jet.Fuel	7.56	0.09	9.45	9.54	13.68	4.05	4.41	6.48	8.1	5.49	76.77
Propane	9.45	0	9.54	8.28	7.65	30.6	4.68	7.02	6.21	5.85	81.72
RBOB.Gasoline	6.75	0	5.85	7.47	4.23	3.6	25.2	8.46	9.09	5.04	70.29
NYH.Gasoline	6.21	0	6.12	6.21	5.76	2.97	6.03	13.32	10.62	4.86	67.86
USGC.Gasoline	6.03	0	5.85	5.76	5.94	2.88	5.94	9.36	13.86	4.68	64.62

TO_ABS	6.12	0.09	6.12	6.12	5.49	3.15	3.96	5.67	5.76	**4.72**	
TO_WTH	84.69	0.99	85.23	84.51	76.05	43.83	55.17	79.38	80.28		**65.56**
Net Spillover (to others - from others)	1.658286	-0.33718	0.491801	0.102316	-0.05178	-2.72548	-1.09023	0.826339	1.125928		

Figure-1: Descriptive Statistics and Pairwise Correlations

Note: This figure demonstrate the correlation matrix of all the series used in empirical analysis. *** denotes the significance at 1% level.

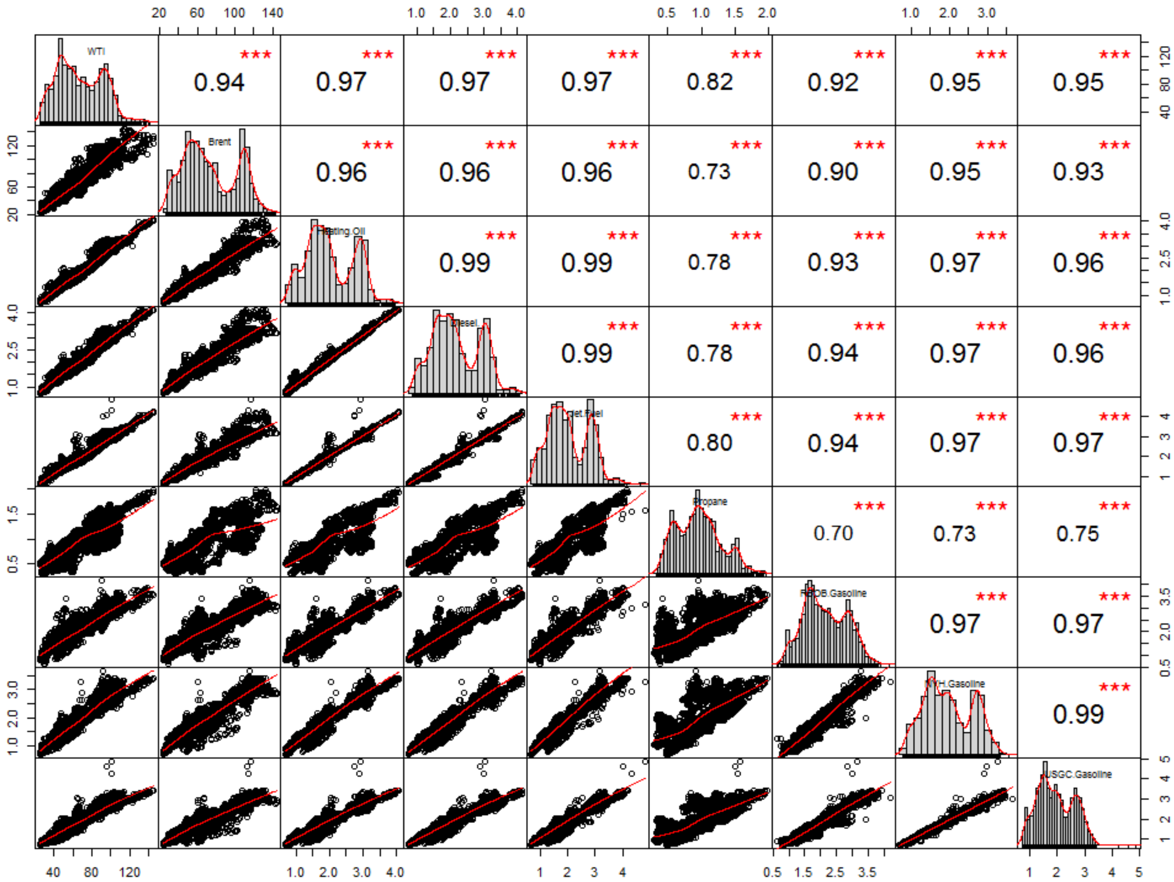


Figure-2: Correlation analysis of log-returns based on clustering algorithm

Note: This figure presents the correlation analysis of log-returns series based on a clustering algorithm. The blue line plots are presented by positive correlation among the series.

Figure-3: Network analysis of correlations among log-returns series

Note: This figure show the network analysis of correlations among log-returns series. There are three types of correlation network analysis presents in this figure i.e. Pearson Correlation Network, Spearman Correlation Network, and Kendall Correlation Network.

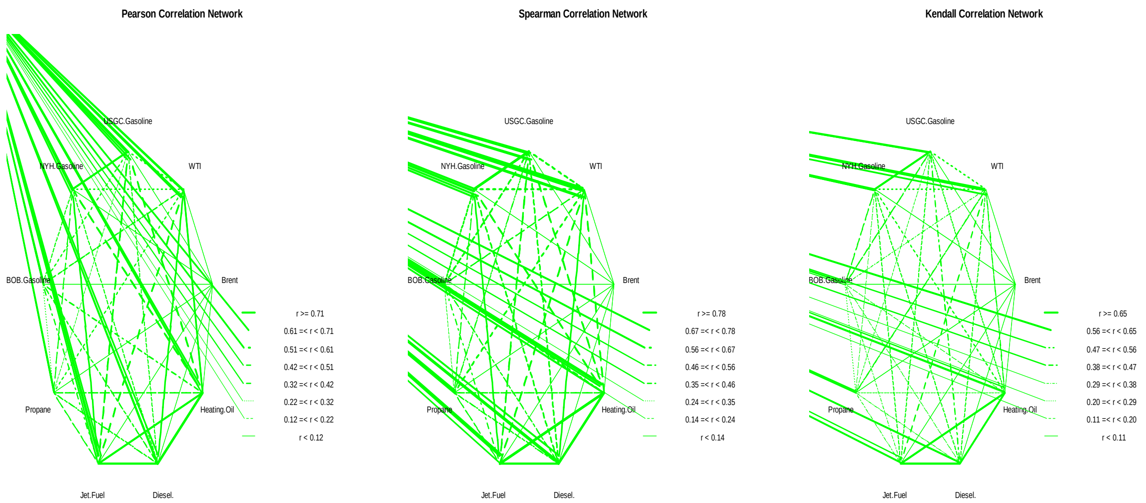


Figure-4: Partial contemporaneous and partial directed correlation analysis

Note: This figure presents two-network analysis i.e. partial contemporaneous and partial directed correlation.

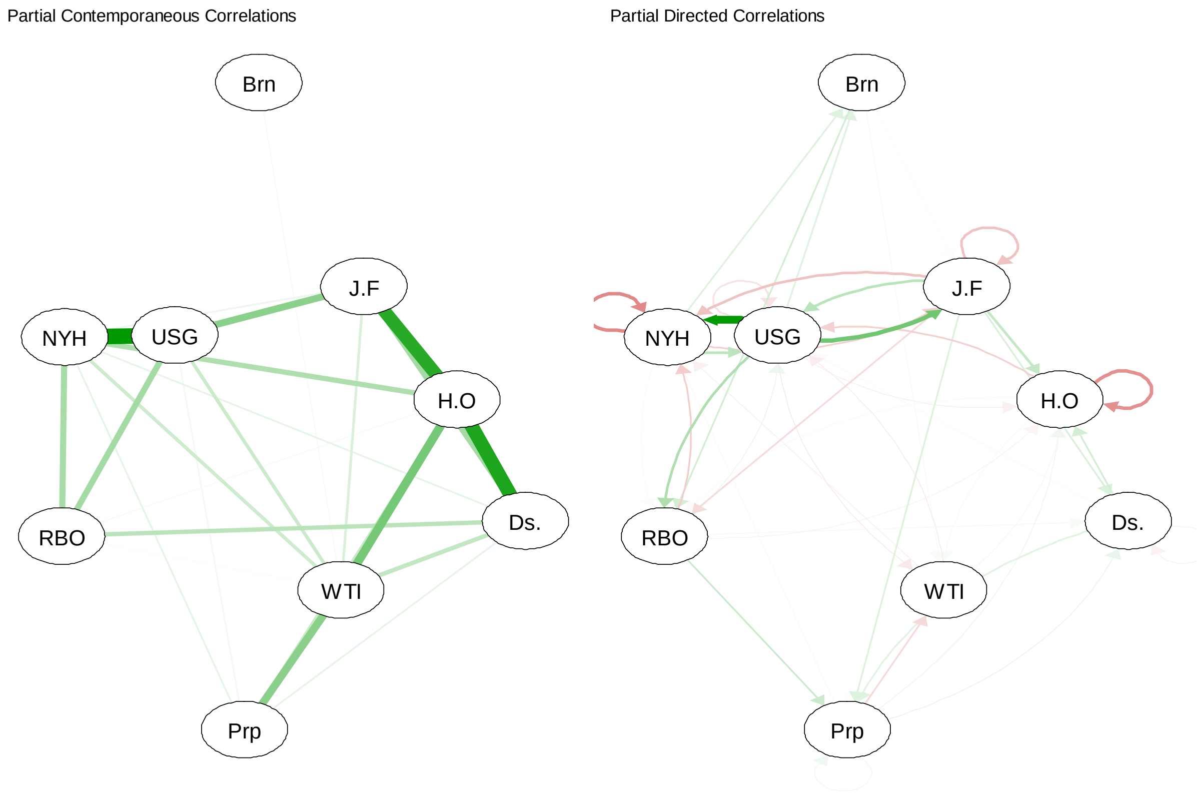


Figure-5: Wavelet multiple correlation between crude oil and petroleum products

Note: This figure shows the Wavelet multiple correlation between crude oil and petroleum products. The blue lines in the graph represent Lower (L) limits and Upper (U) respectively at a 95% confidence interval.

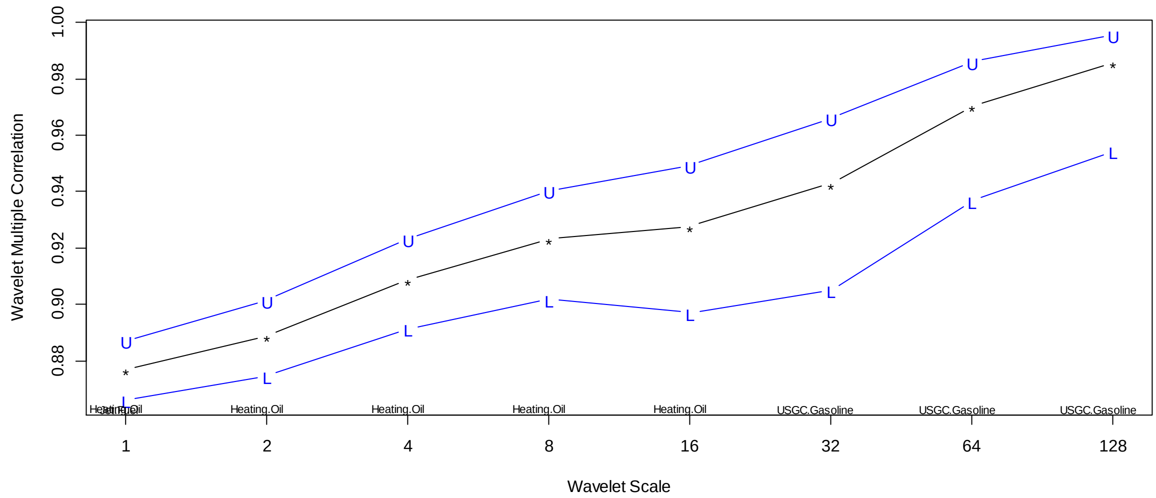


Figure-6: Wavelet multiple cross-correlation between crude oil and petroleum products

Note: This figure shows the Wavelet multiple cross-correlation between crude oil and petroleum products. The blue lines in the graph represent Lower (L) limits and Upper (U) respectively at a 95% confidence interval.

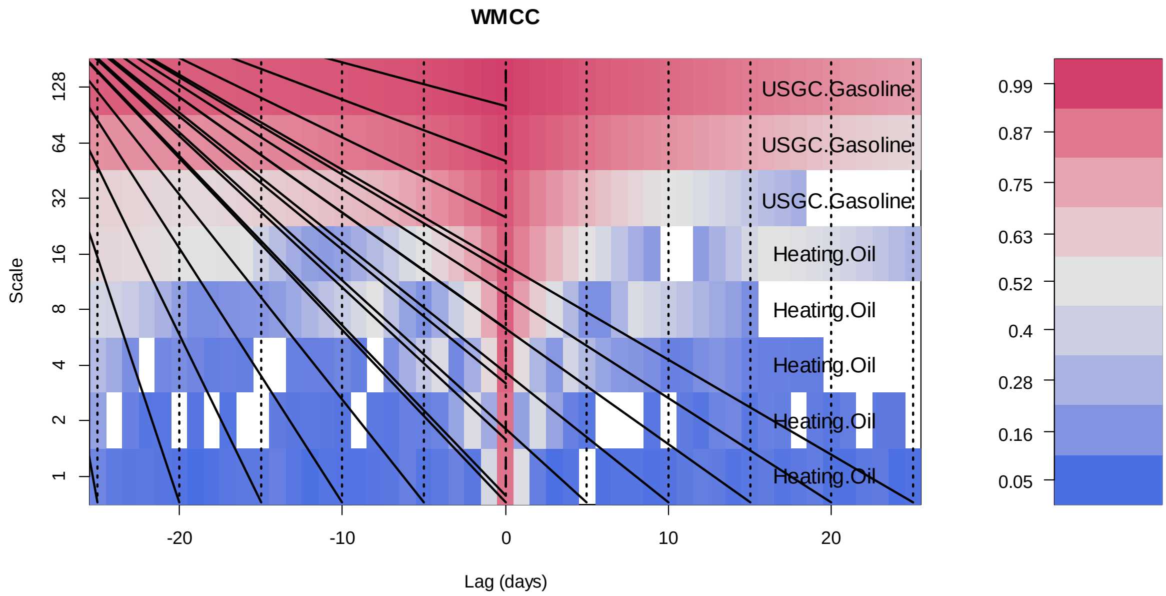


Figure-7: Wavelet multiple cross correlations

Note: This figure presents the results for wavelet multiple cross-correlations for multiple time scales with leads and lags up to a month trading period. In the figure, every wavelet scale plot displays at its upper-right corner the variable that maximizes the multiple correlations against a linear combination of the rest of variables. The lower and upper bounds are denoted with redlines at a 95% confidence interval.

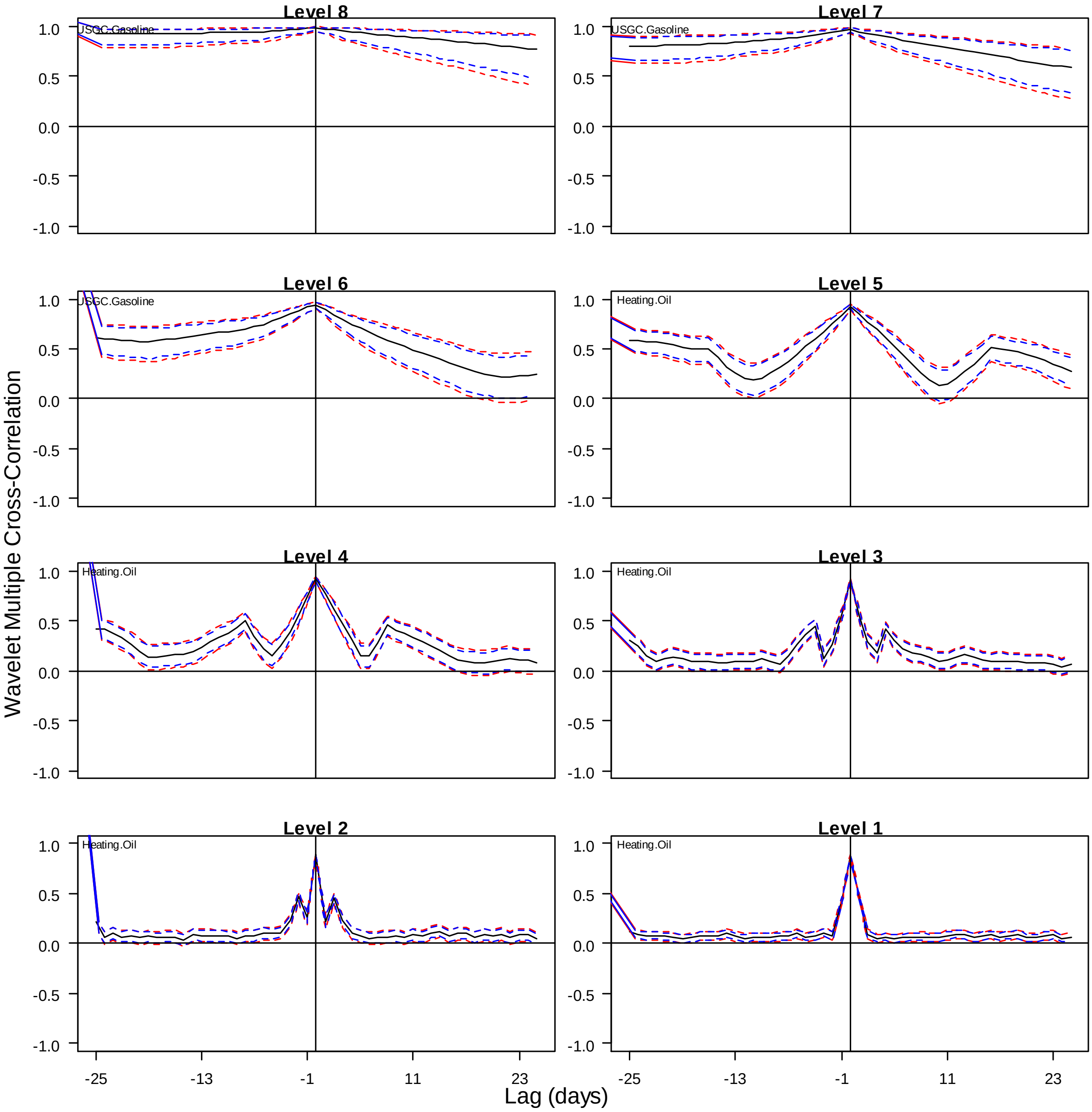


Figure-8: DY overall spillover among considered series

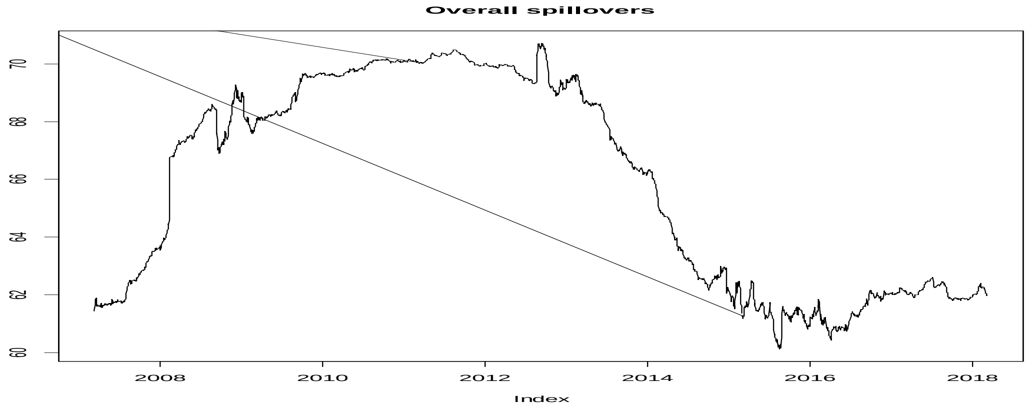


Figure-9: DY To spillovers among considered series

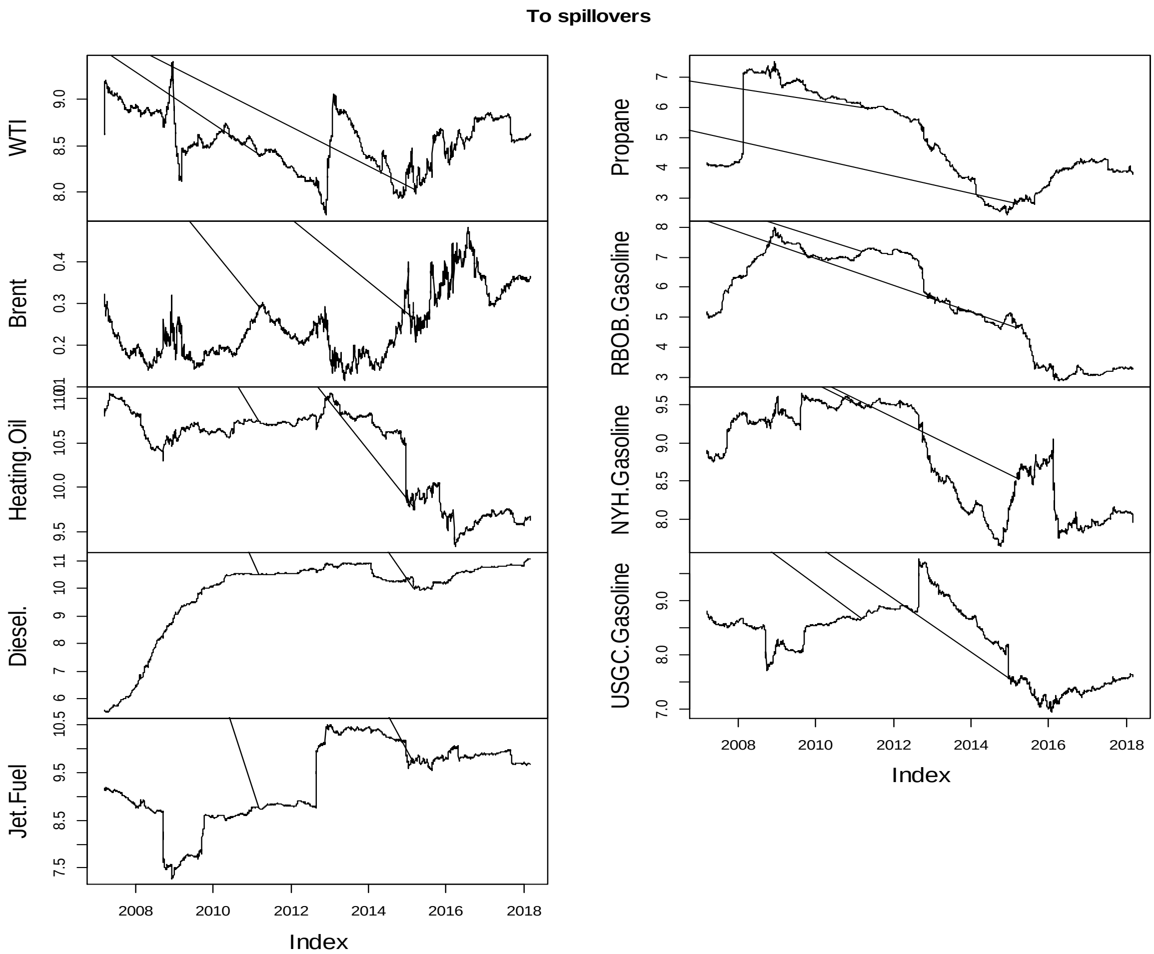


Figure-10: DY from Spillovers among considered series

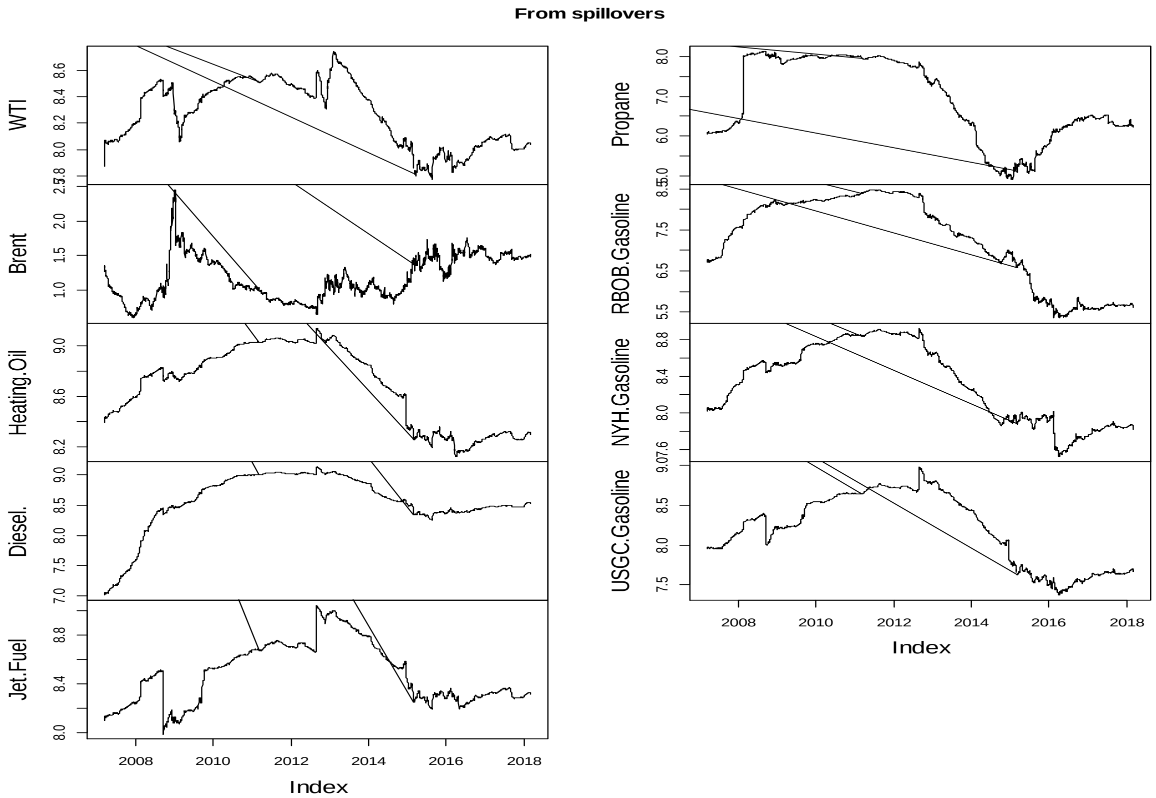


Figure-11: DY Net Spillovers among considered series

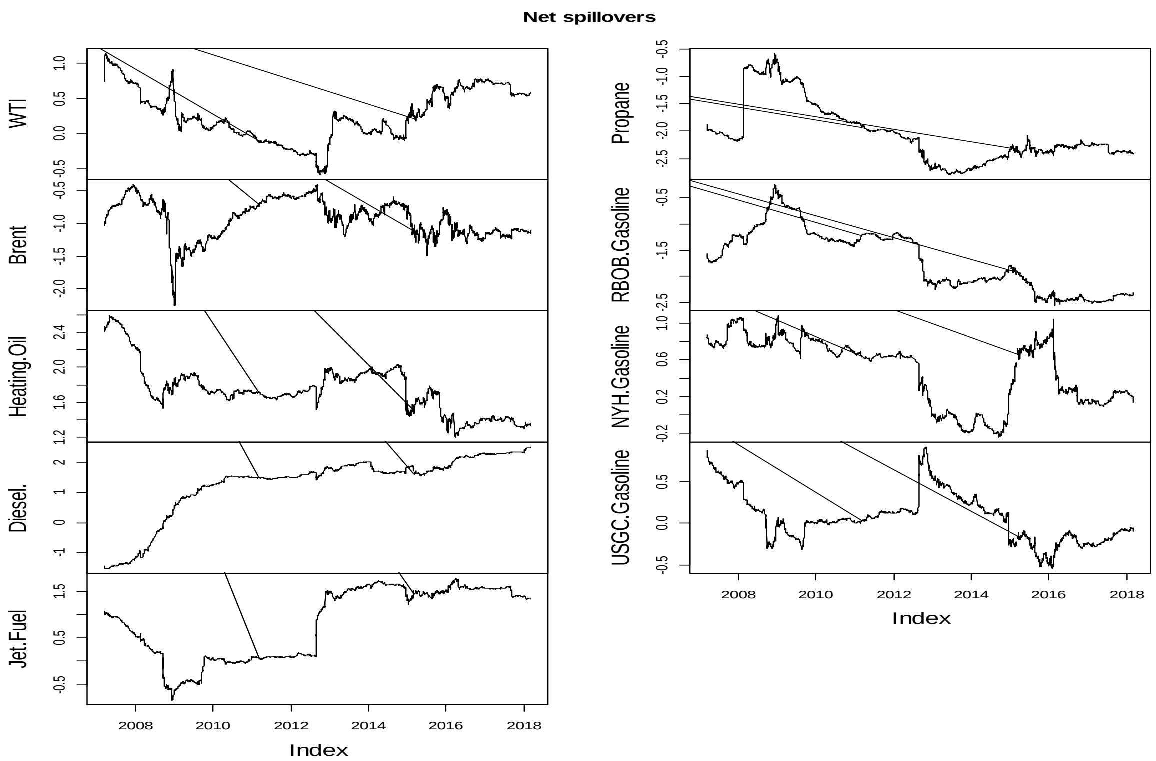
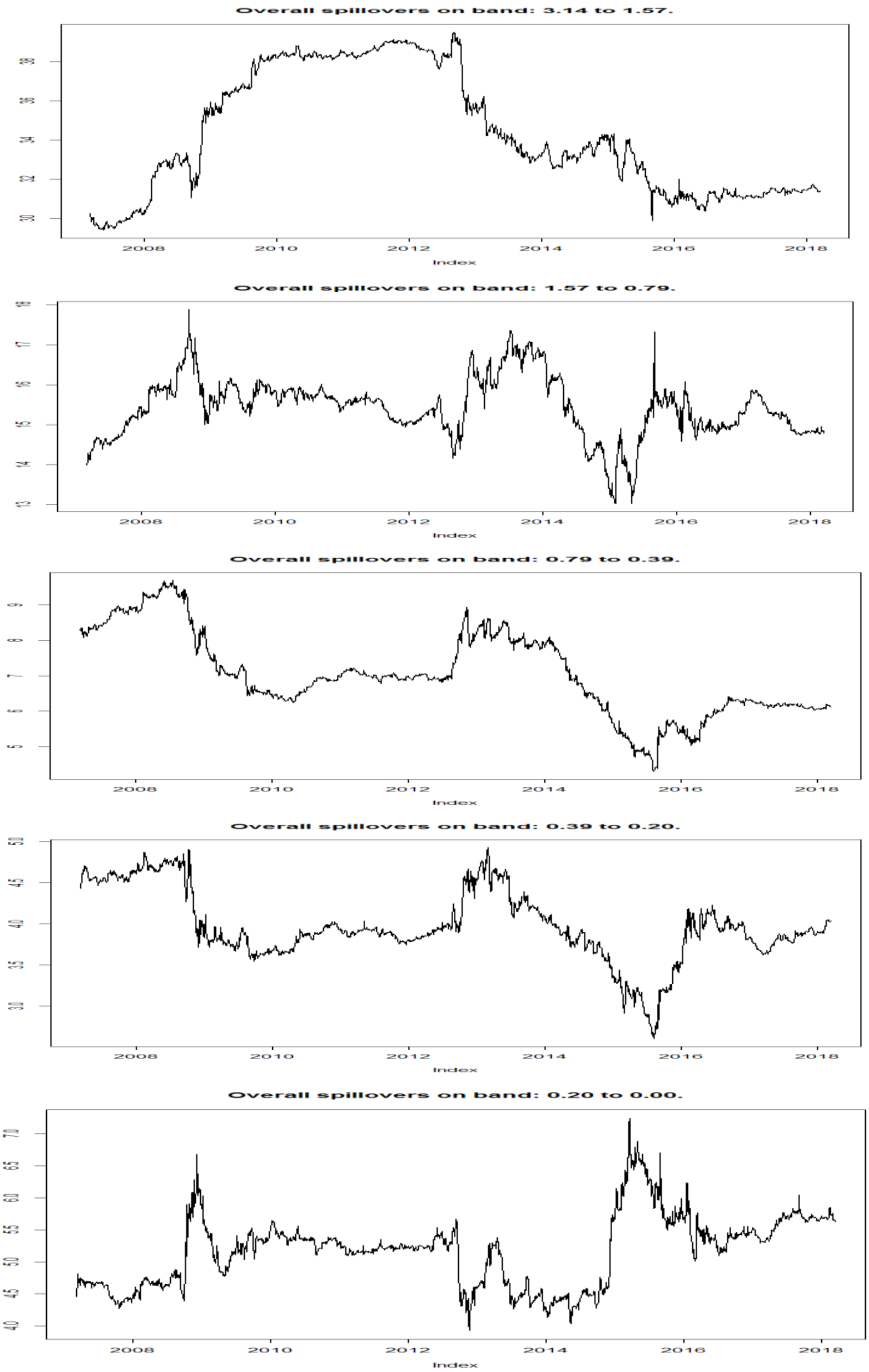


Figure-12: BK overall spillover among considered series

Note: These figures present the time series graph of the overall directional connectedness at different frequency bands. The details about these frequency bands are presented in Table 3.



Appendix A

Note: This Table presents the details about the data used in the analysis of this paper.

Data 1: Crude Oil		
Cushing, OK WTI Spot Price FOB (Dollars per Barrel)	Europe Brent Spot Price FOB (Dollars per Barrel)	
Data 2: Conventional Gasoline		
New York Harbor Conventional Gasoline Regular Spot Price FOB (Dollars per Gallon)	U.S. Gulf Coast Conventional Gasoline Regular Spot Price FOB (Dollars per Gallon)	
Data 3: RBOB Regular Gasoline		
Los Angeles Reformulated RBOB Regular Gasoline Spot Price (Dollars per Gallon)		
Data 4: No. 2 Heating Oil		
New York Harbor No. 2 Heating Oil Spot Price FOB (Dollars per Gallon)		
Data 5: Ultra-Low-Sulfur No. 2 Diesel Fuel		
New York Harbor Ultra-Low Sulfur No 2 Diesel Spot Price (Dollars per Gallon)	U.S. Gulf Coast Ultra-Low Sulfur No 2 Diesel Spot Price (Dollars per Gallon)	Los Angeles, CA Ultra-Low Sulfur CARB Diesel Spot Price (Dollars per Gallon)
Data 6: Kerosene-Type Jet Fuel		
U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price FOB (Dollars per Gallon)		
Data 7: Propane		
Mont Belvieu, TX Propane Spot Price FOB (Dollars per Gallon)		

Appendix B

Figure-B1: Time series plot of log-level data

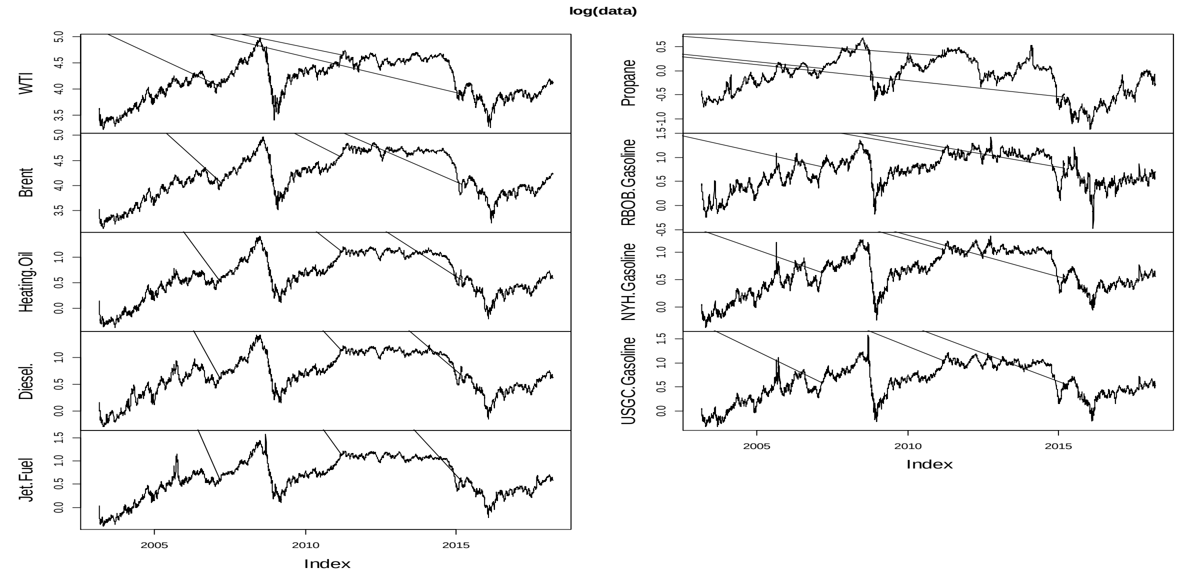
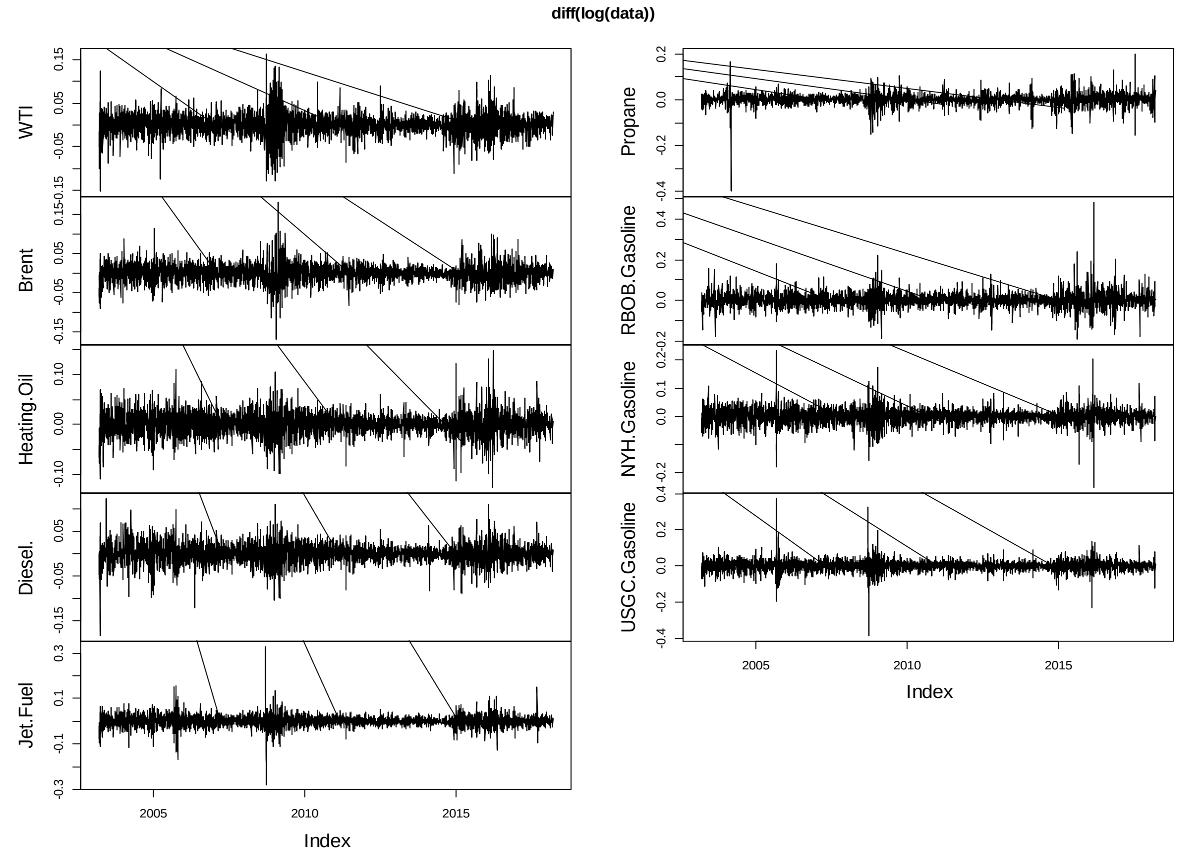
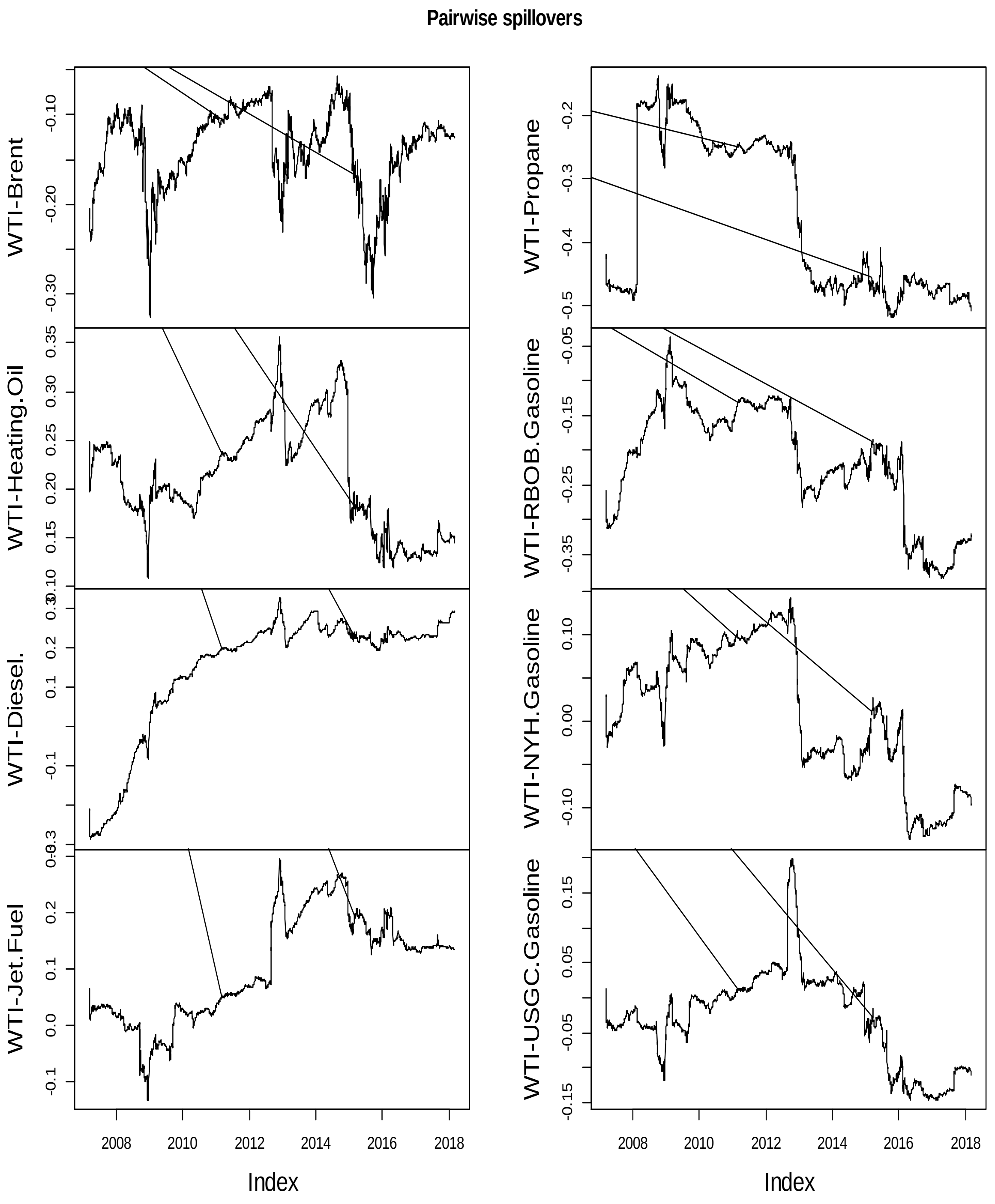


Figure-B2: Time series plot of log-returns data

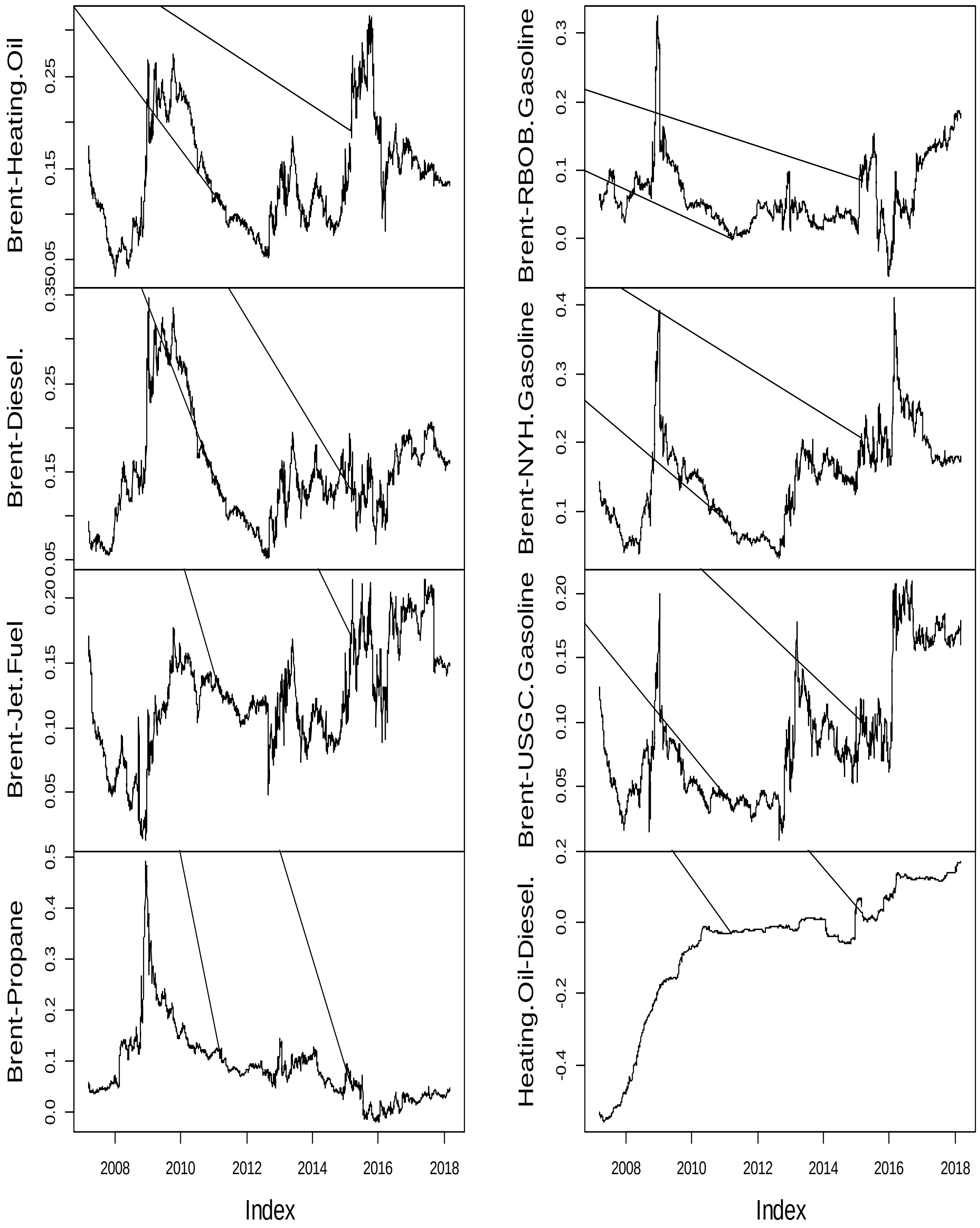


Appendix C

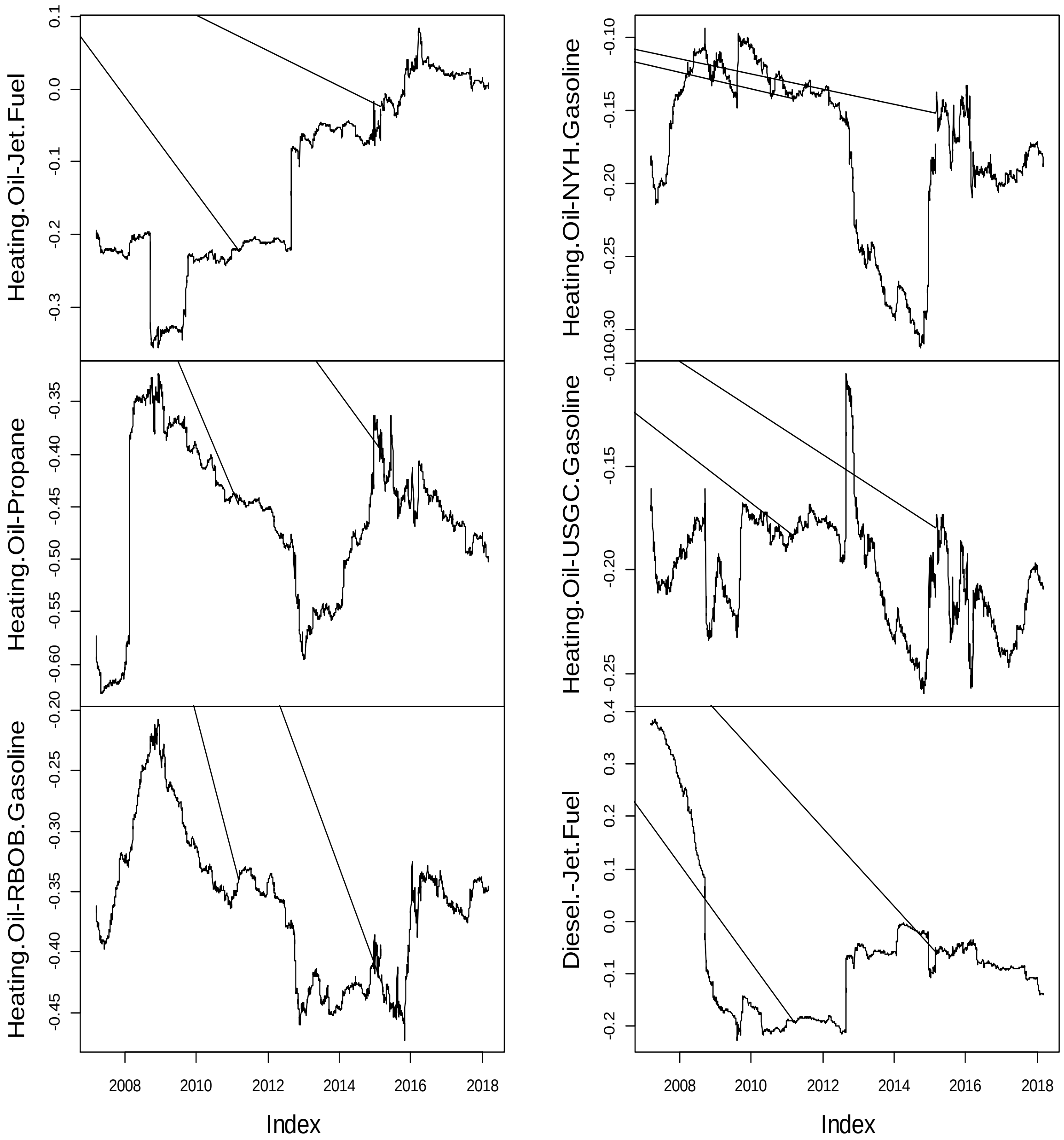
Figure C1: DY Pairwise Spillovers among considered series

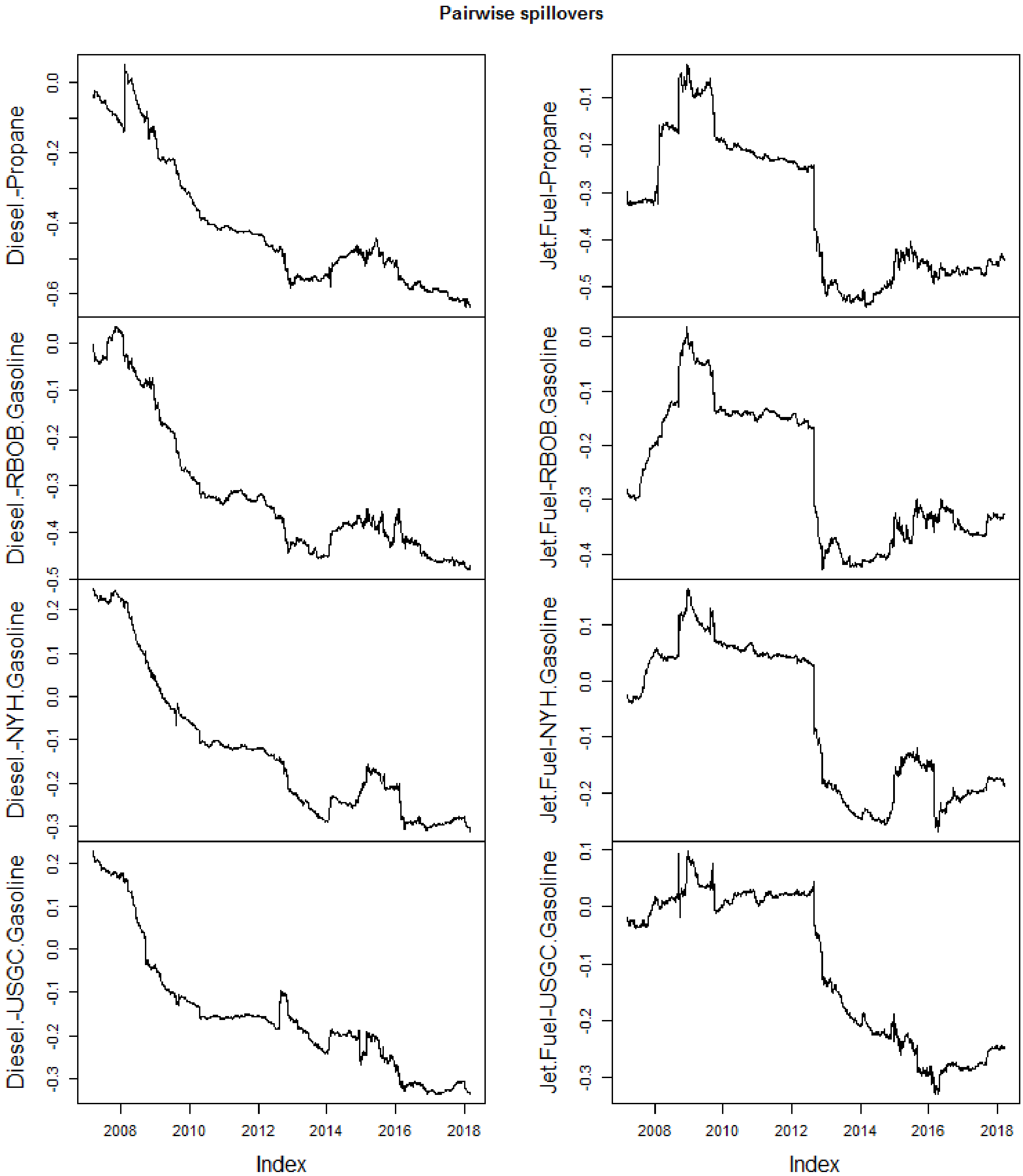


Pairwise spillovers

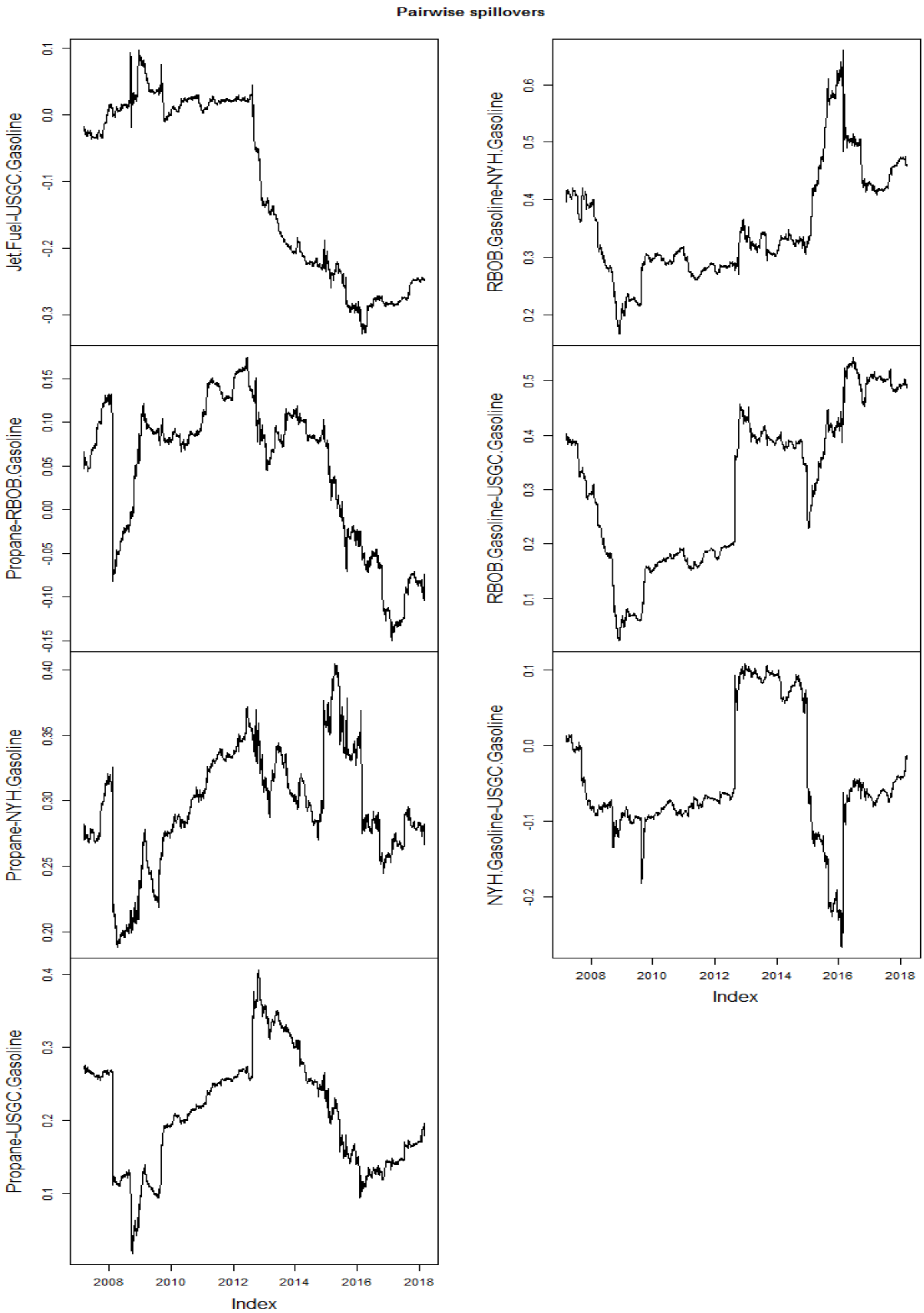


Pairwise spillovers





Pairwise spillovers
Diesel.-Propane
Diesel.-RBOB.Gasoline
Diesel.-NYH.Gasoline
Diesel.-USGC.Gasoline
Jet.Fuel-Propane
Jet.Fuel-RBOB.Gasoline
Jet.Fuel-NYH.Gasoline
Jet.Fuel-USGC.Gasoline
2008
2010
2012
2014
2016
2018
Index

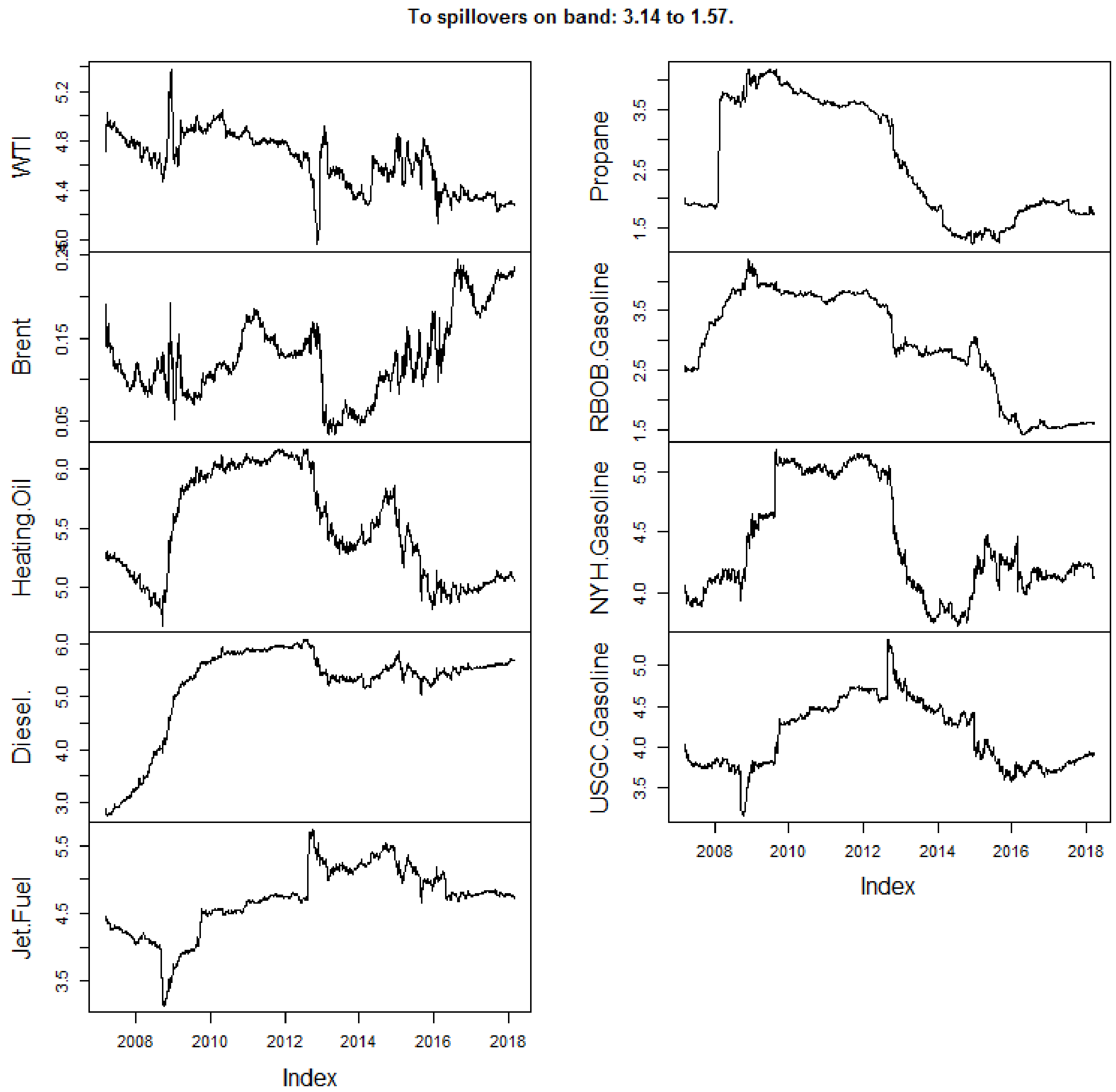


Pairwise spillovers
Jet.Fuel-USGC.Gasoline
Propane-RBOB.Gasoline
Propane-NYH.Gasoline
Propane-USGC.Gasoline
RBOB.Gasoline-NYH.Gasoline
RBOB.Gasoline-USGC.Gasoline
NYH.Gasoline-USGC.Gasoline
2008
2010
2012
2014
2016
2018
Index

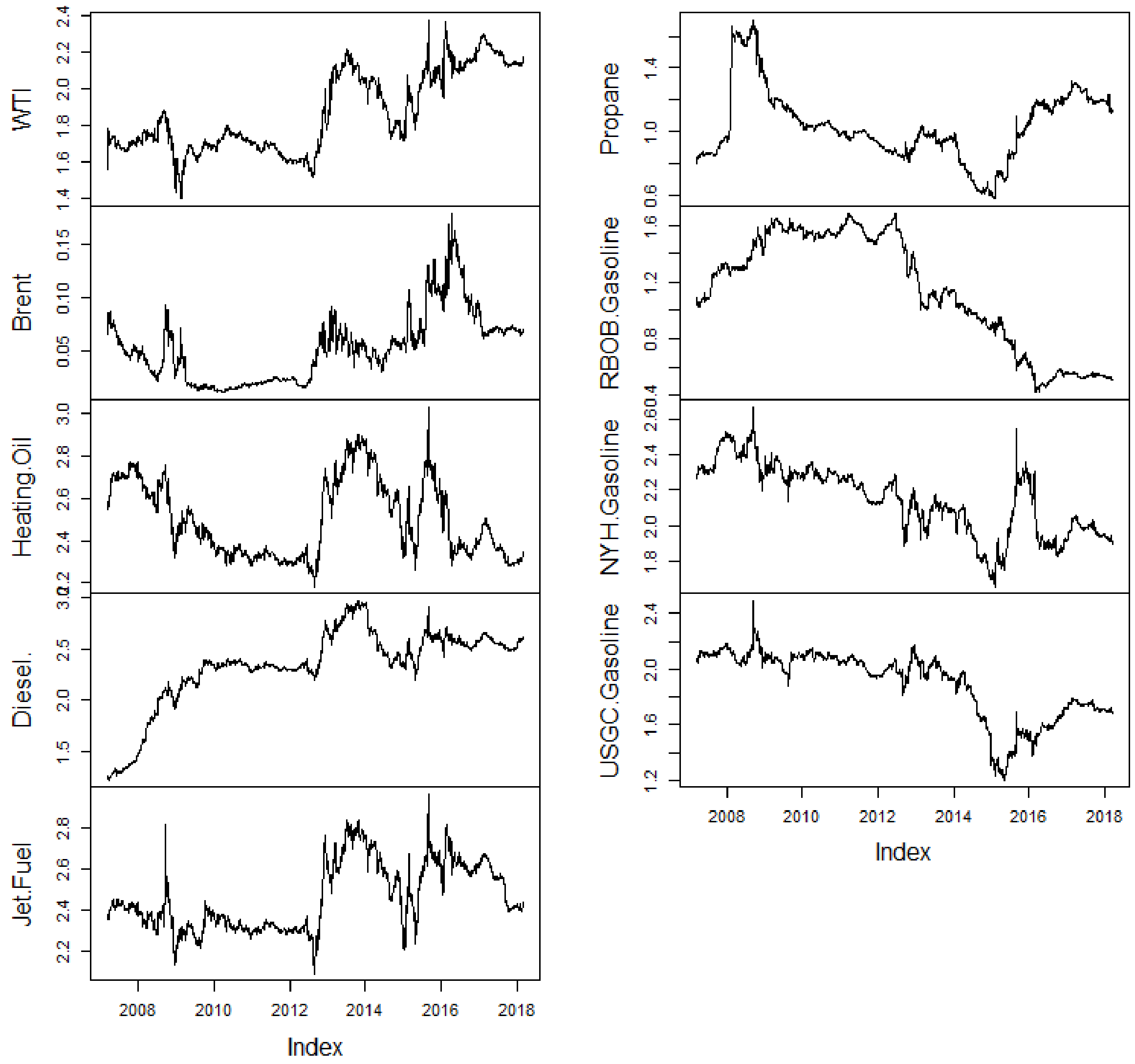
Results for Frequency Domain Spillover

Appendix D

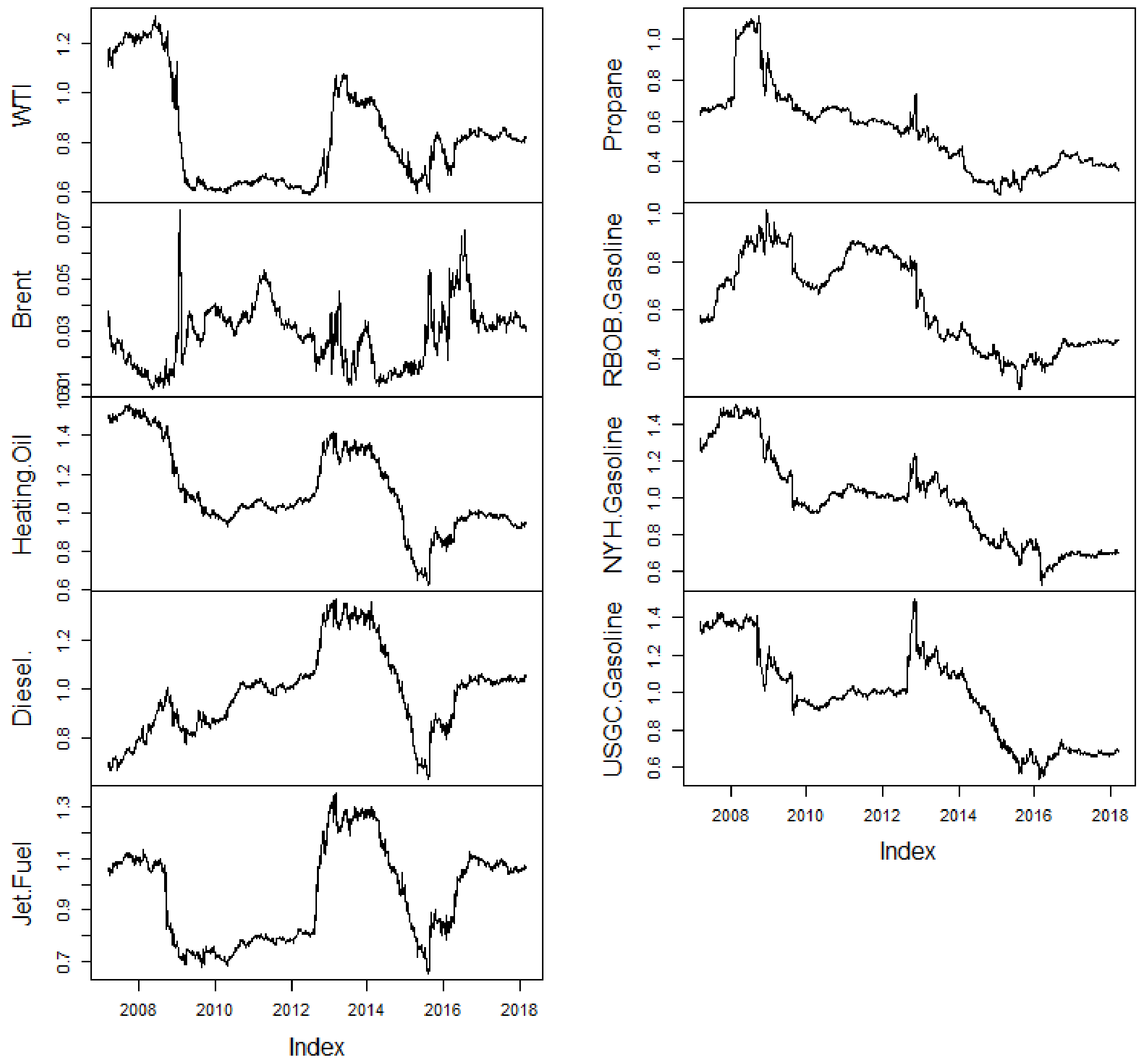
Figure D1: DY TO spillover among considered series



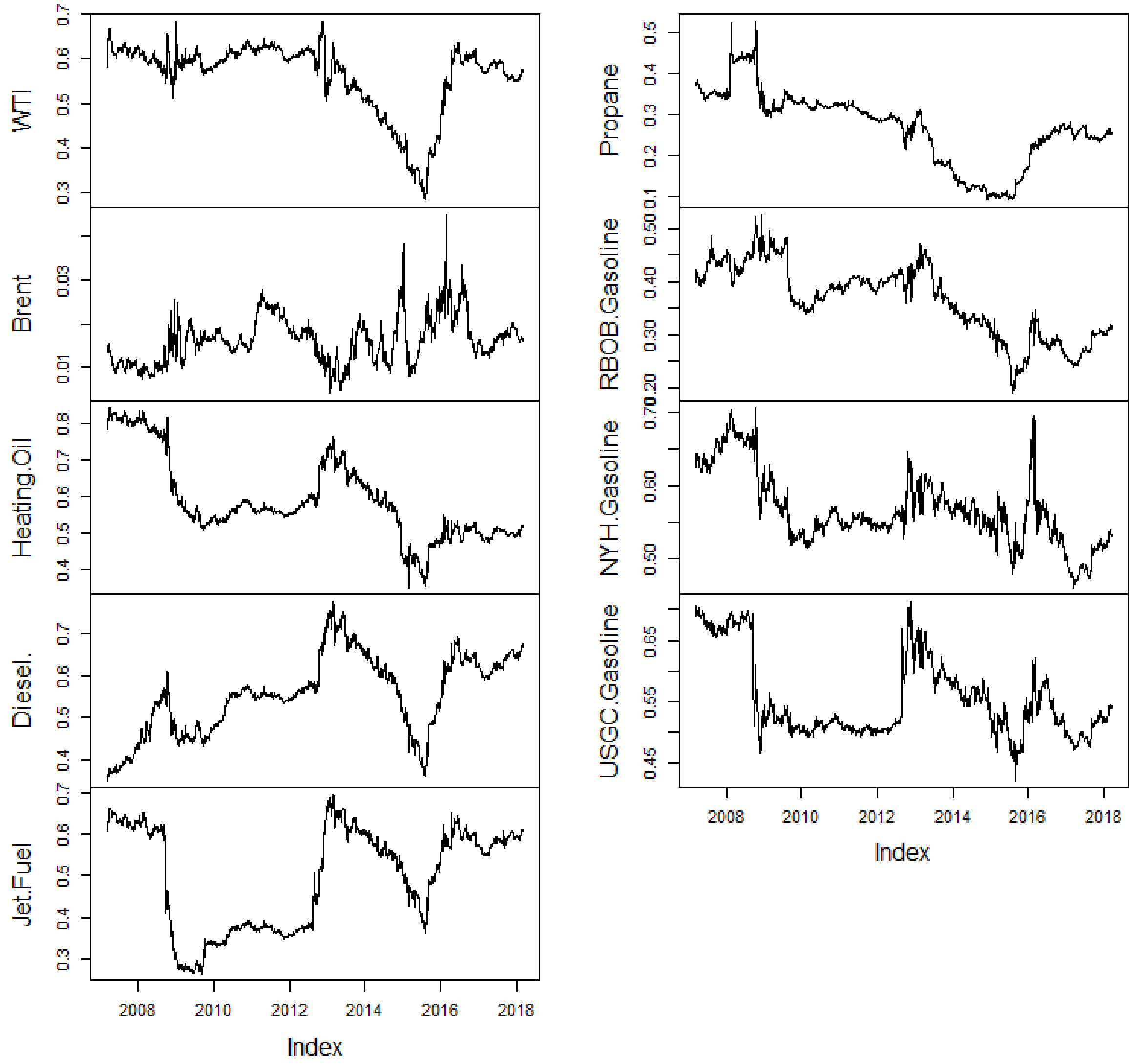
To spillovers on band: 1.57 to 0.79.



To spillovers on band: 0.79 to 0.39.



To spillovers on band: 0.39 to 0.20.



To spillovers on band: 0.20 to 0.00.

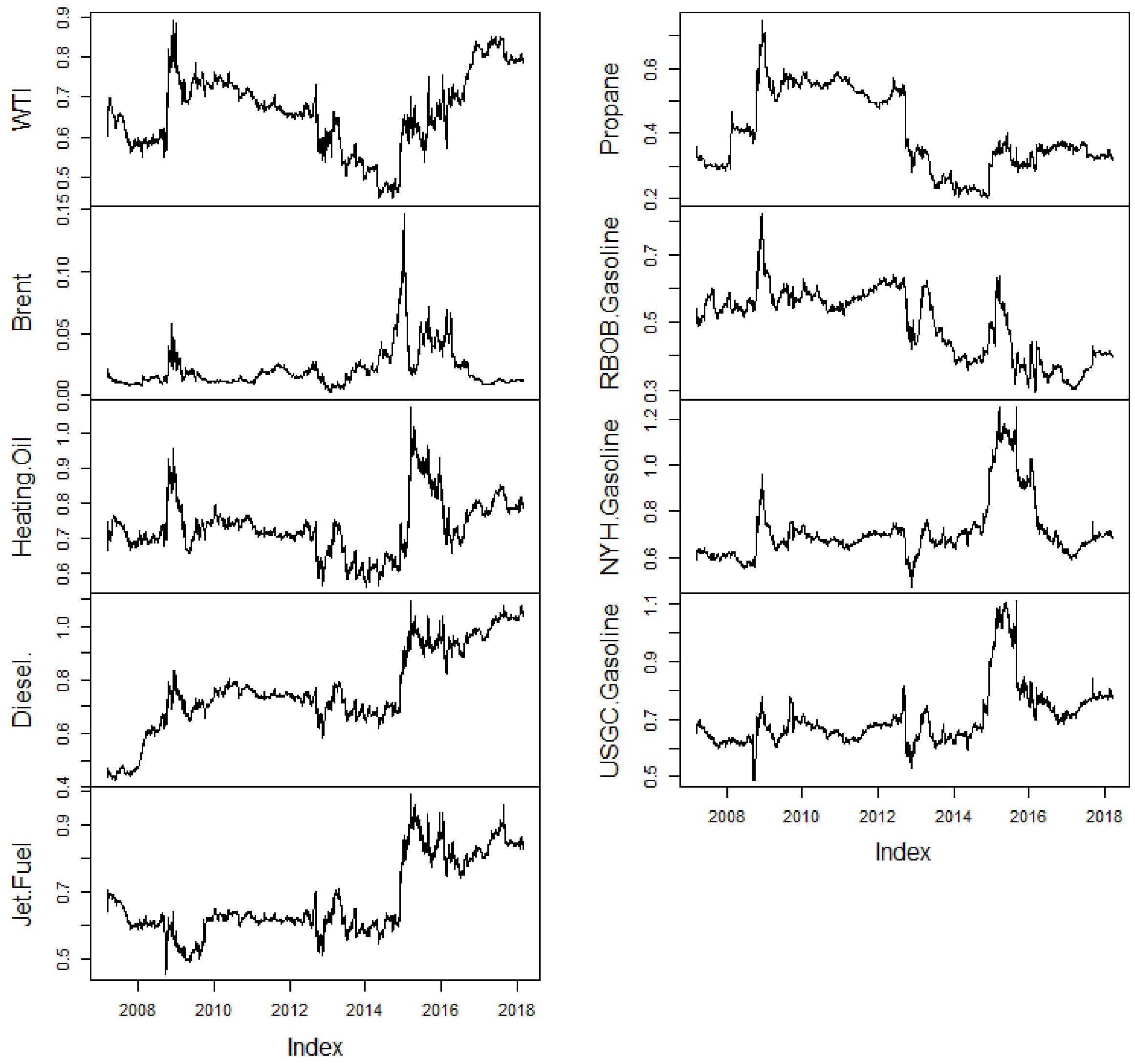
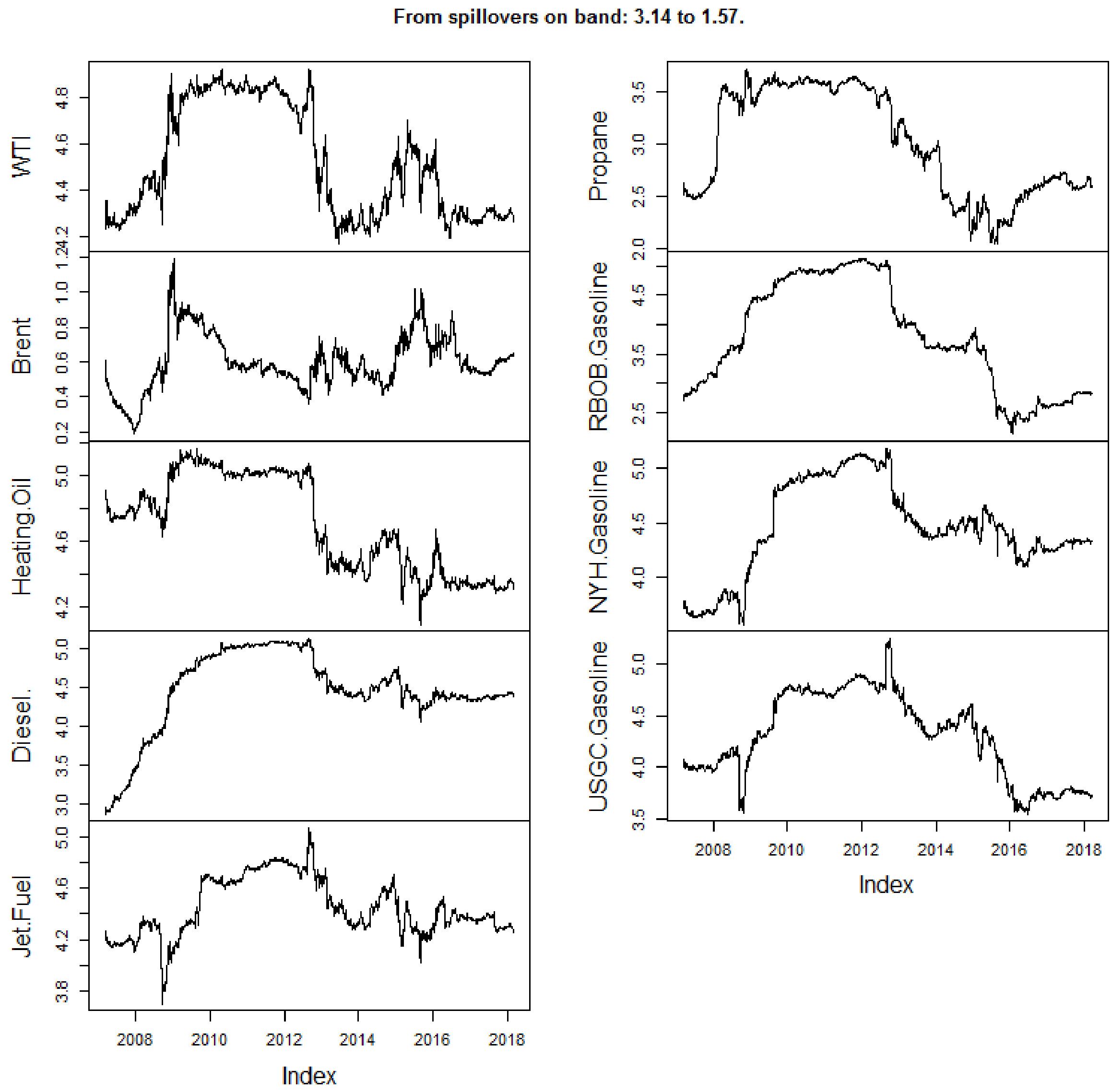
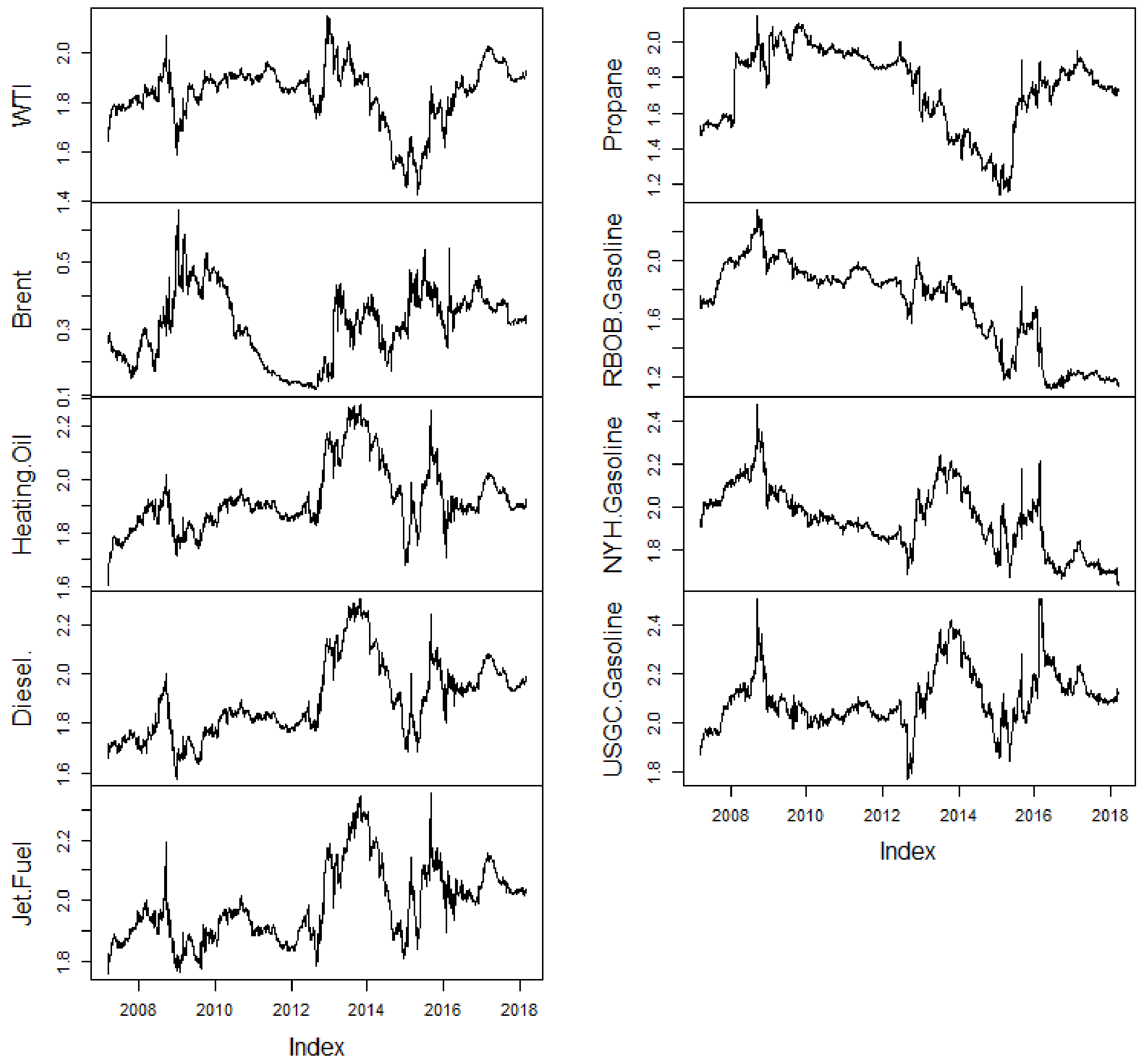


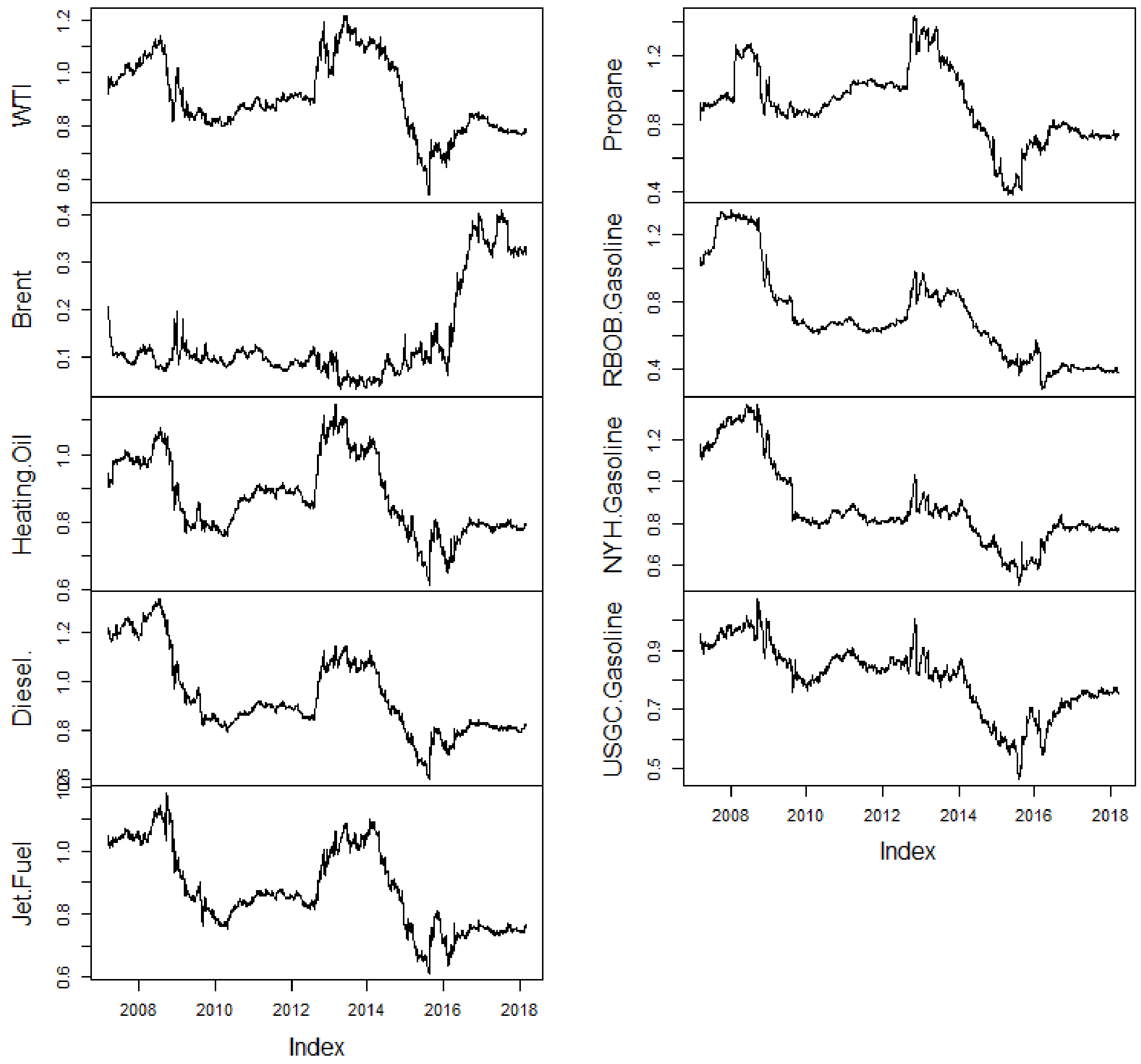
Figure D2: DY From spillover among considered series



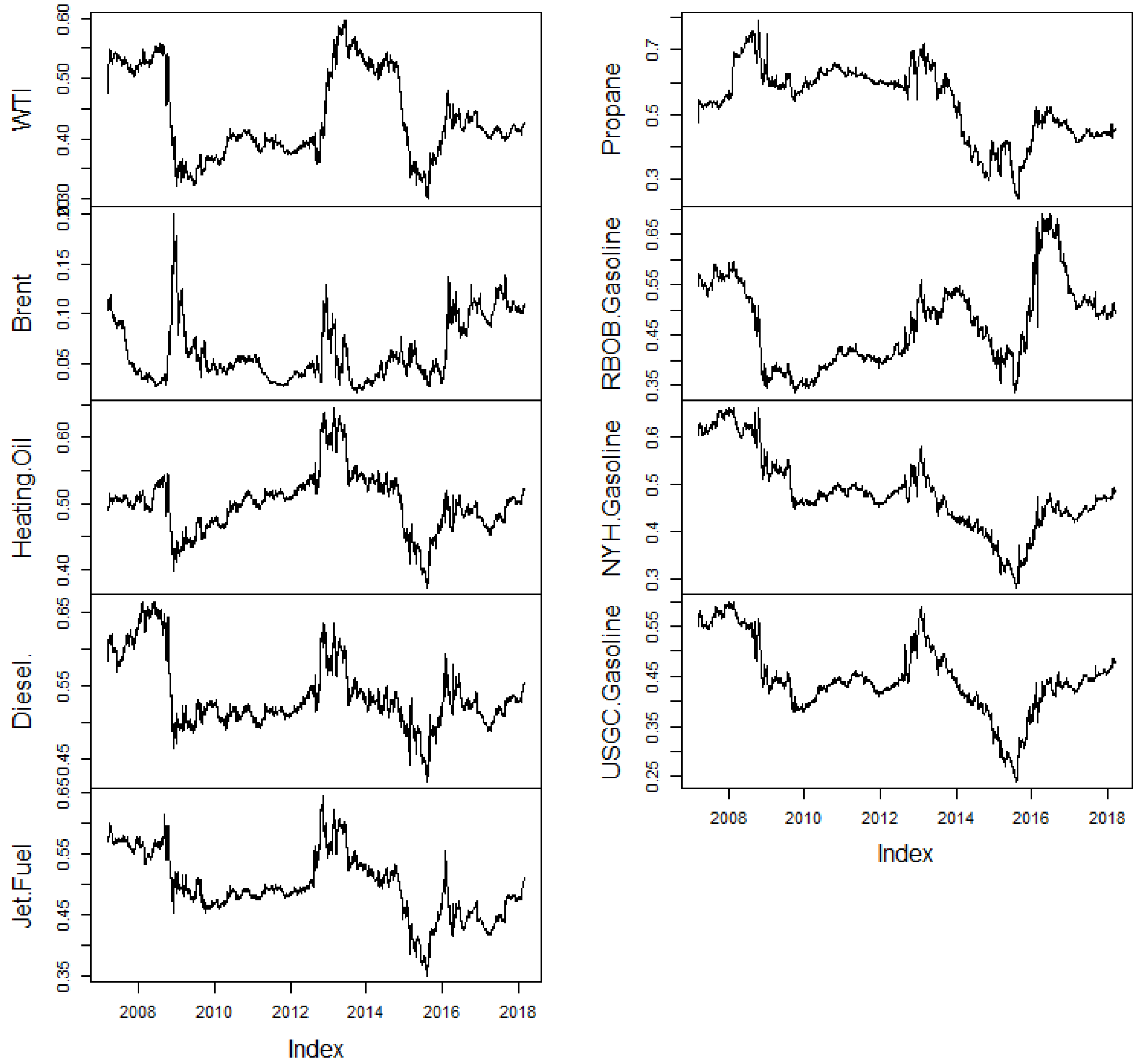
From spillovers on band: 1.57 to 0.79.



From spillovers on band: 0.79 to 0.39.



From spillovers on band: 0.39 to 0.20.



From spillovers on band: 0.20 to 0.00.

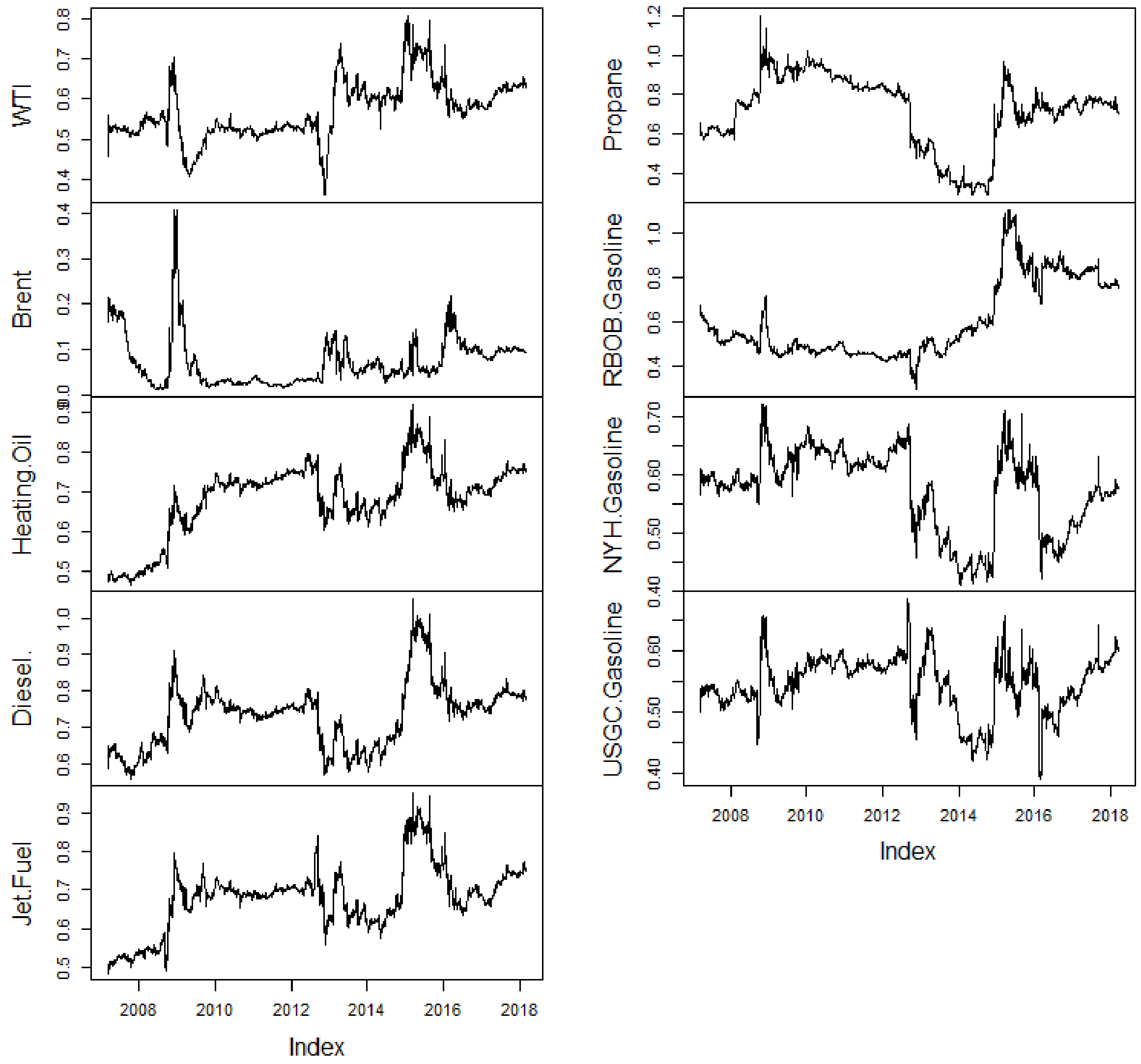
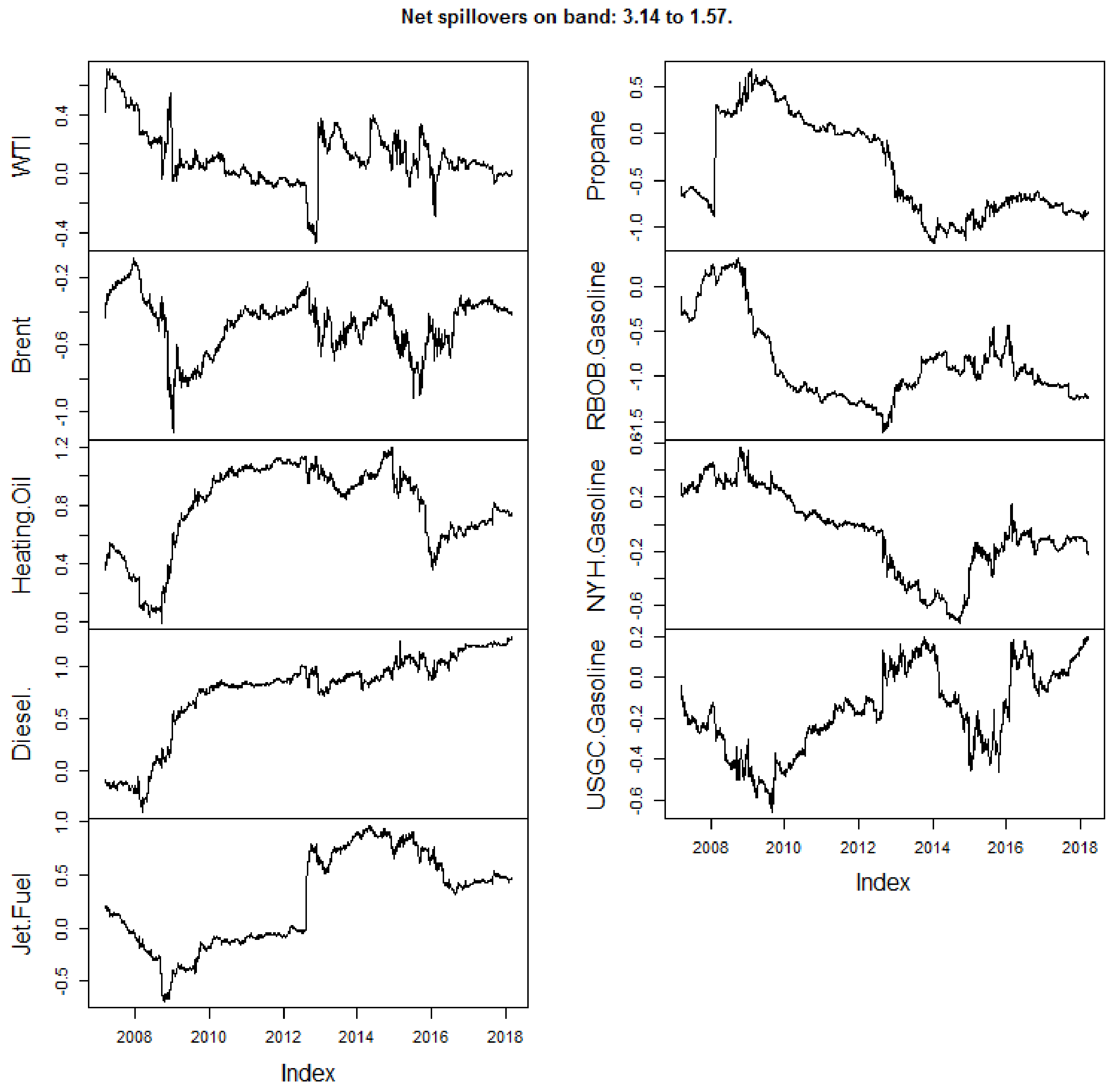
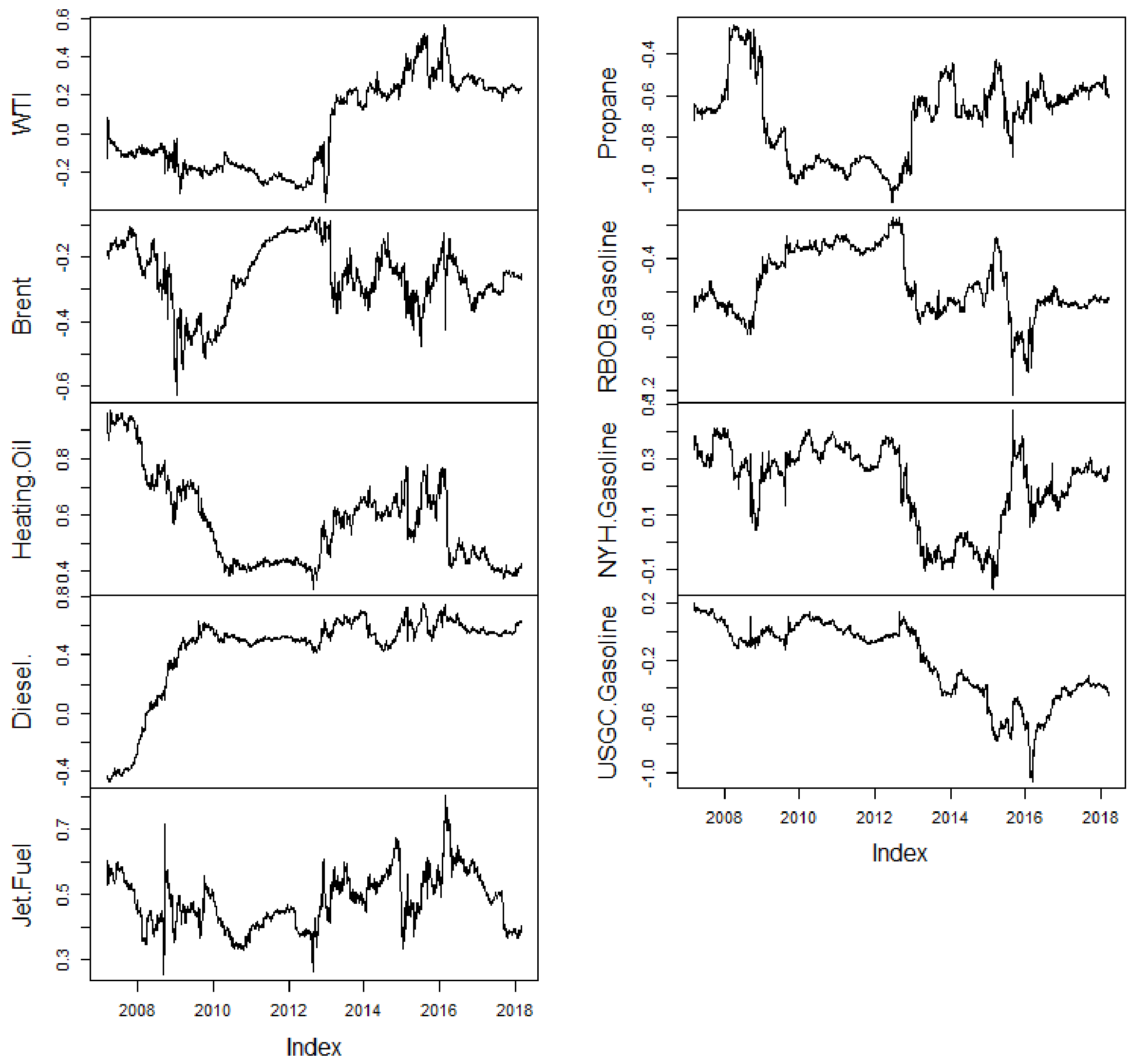


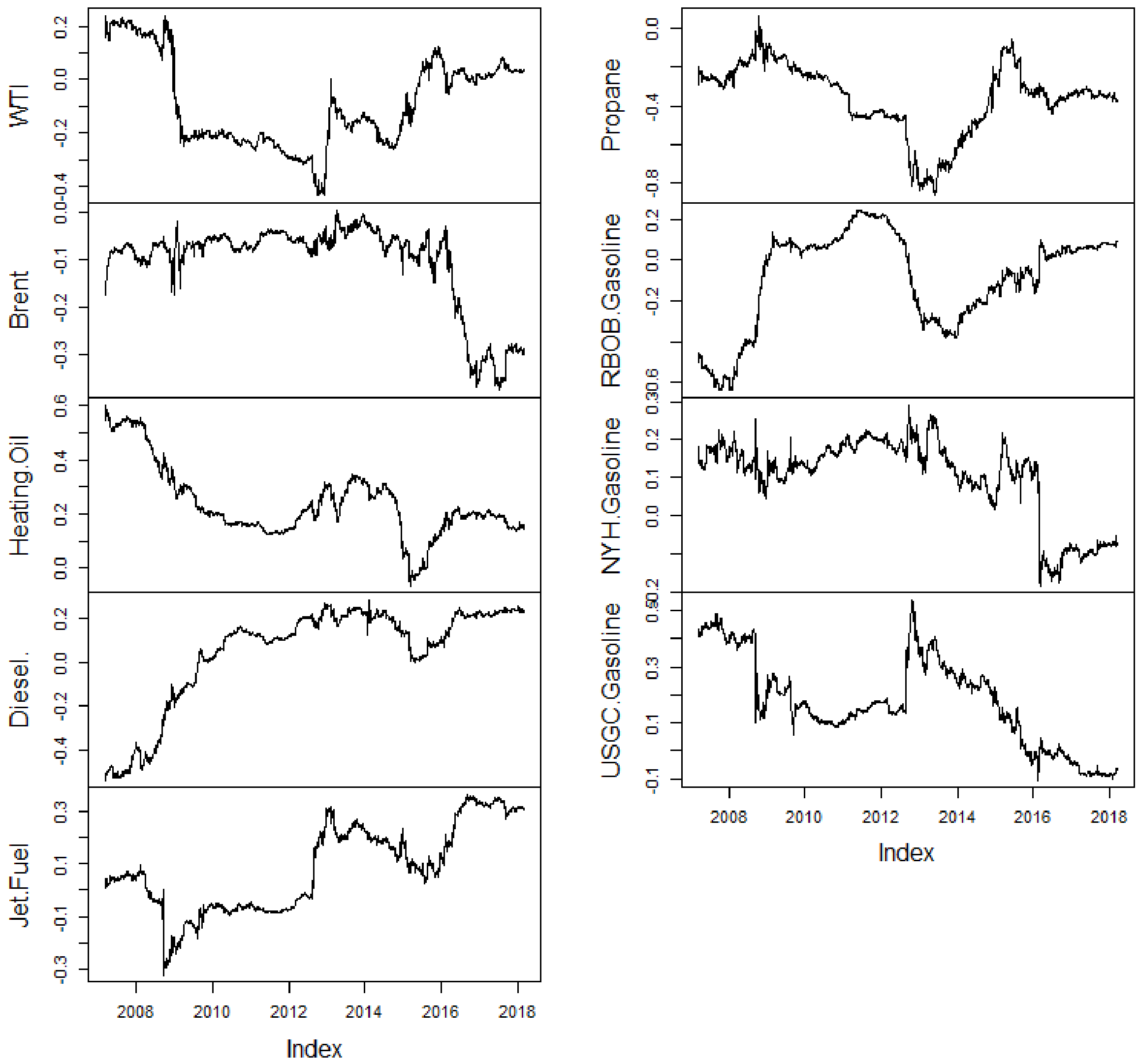
Figure D3: DY Net spillover among considered series



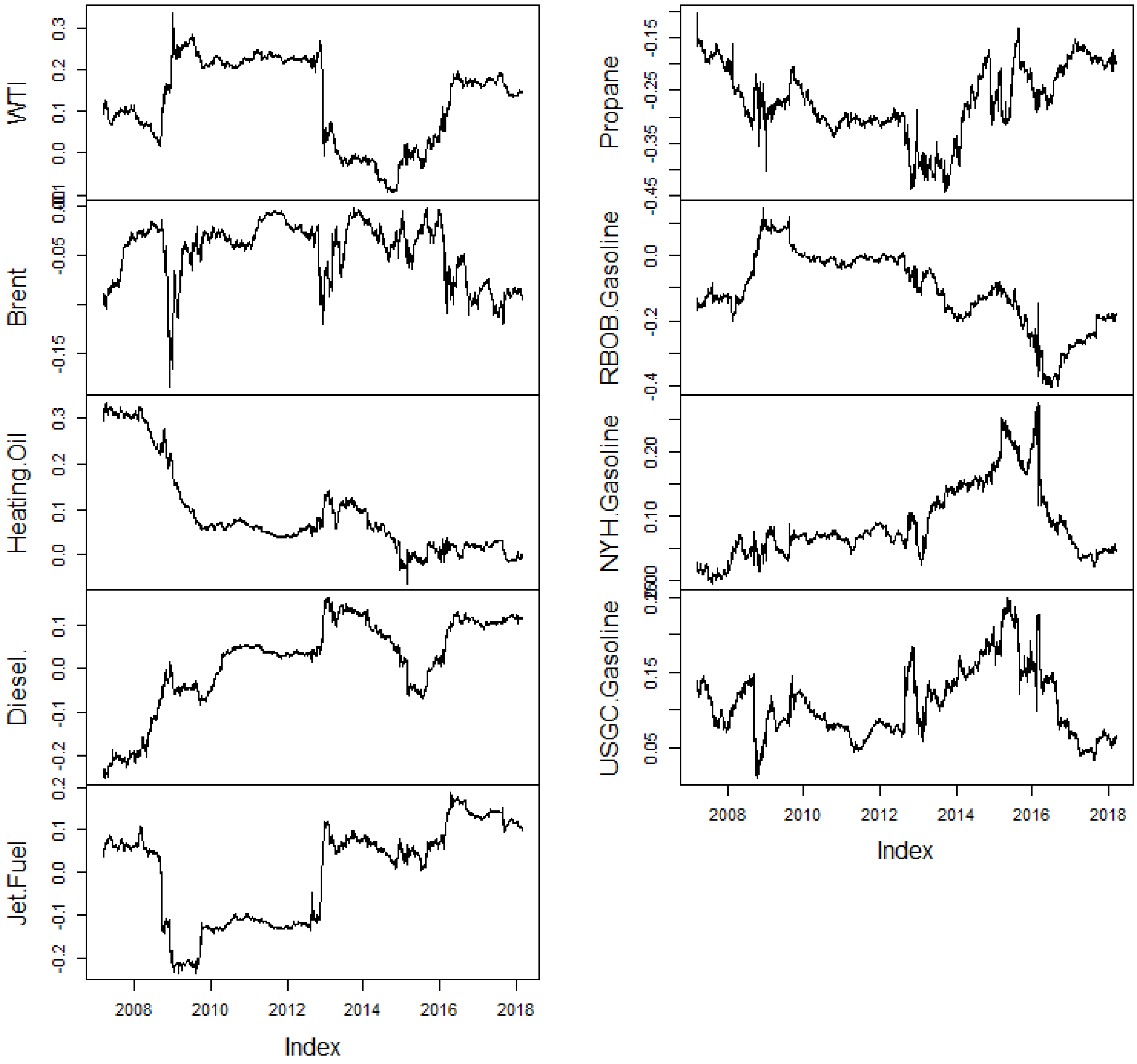
Net spillovers on band: 1.57 to 0.79.



Net spillovers on band: 0.79 to 0.39.



Net spillovers on band: 0.39 to 0.20.



Net spillovers on band: 0.20 to 0.00.

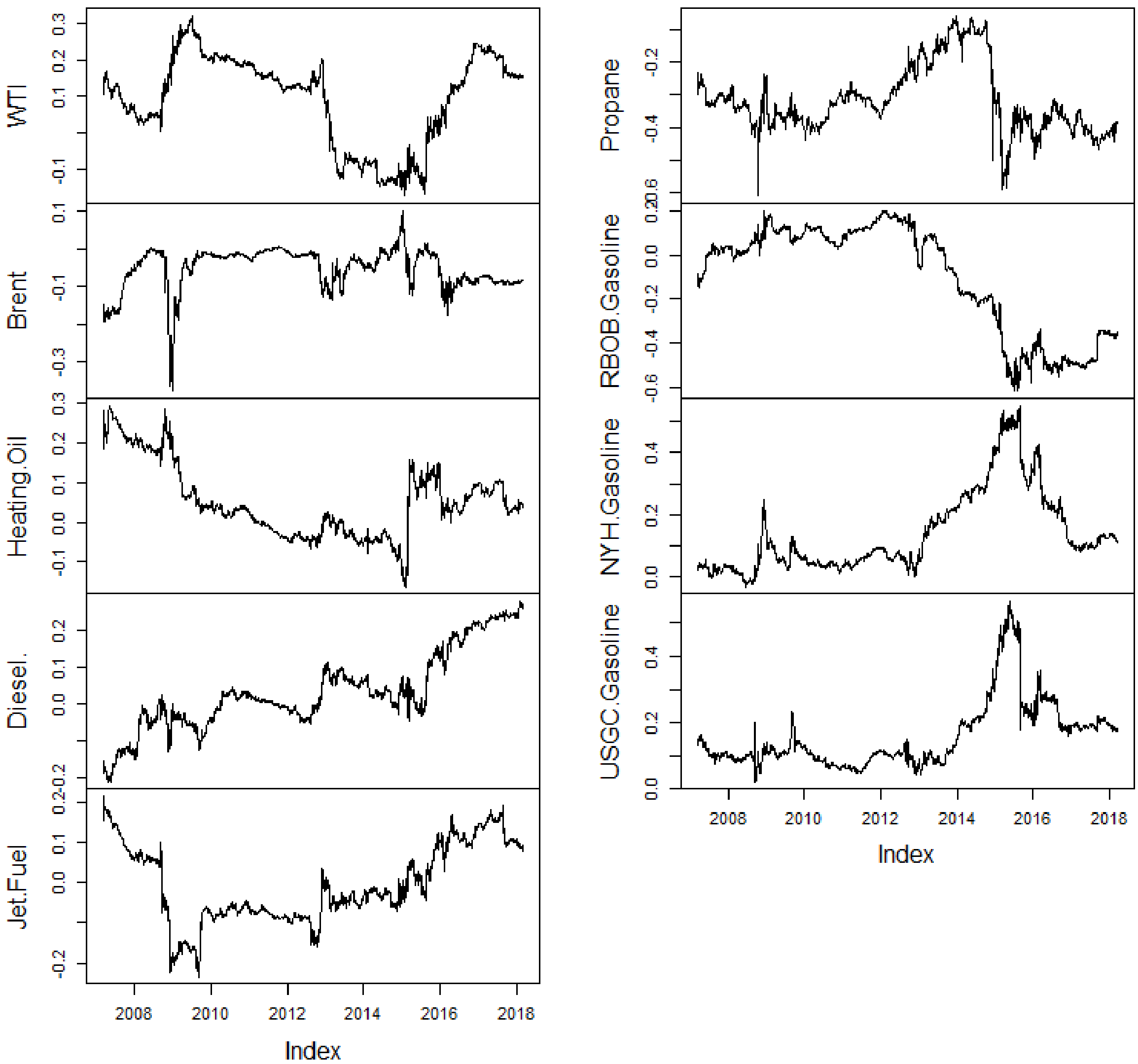
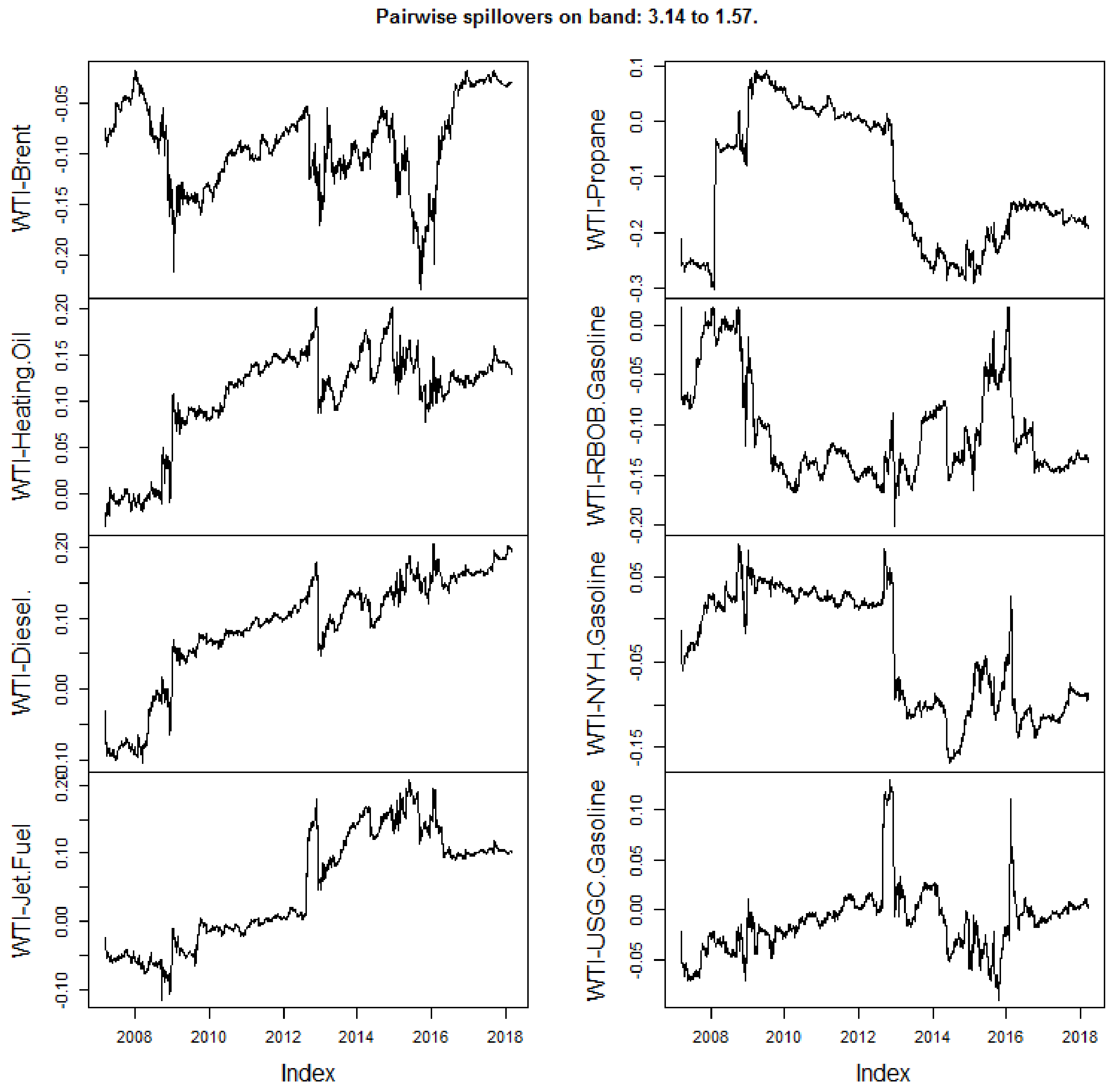
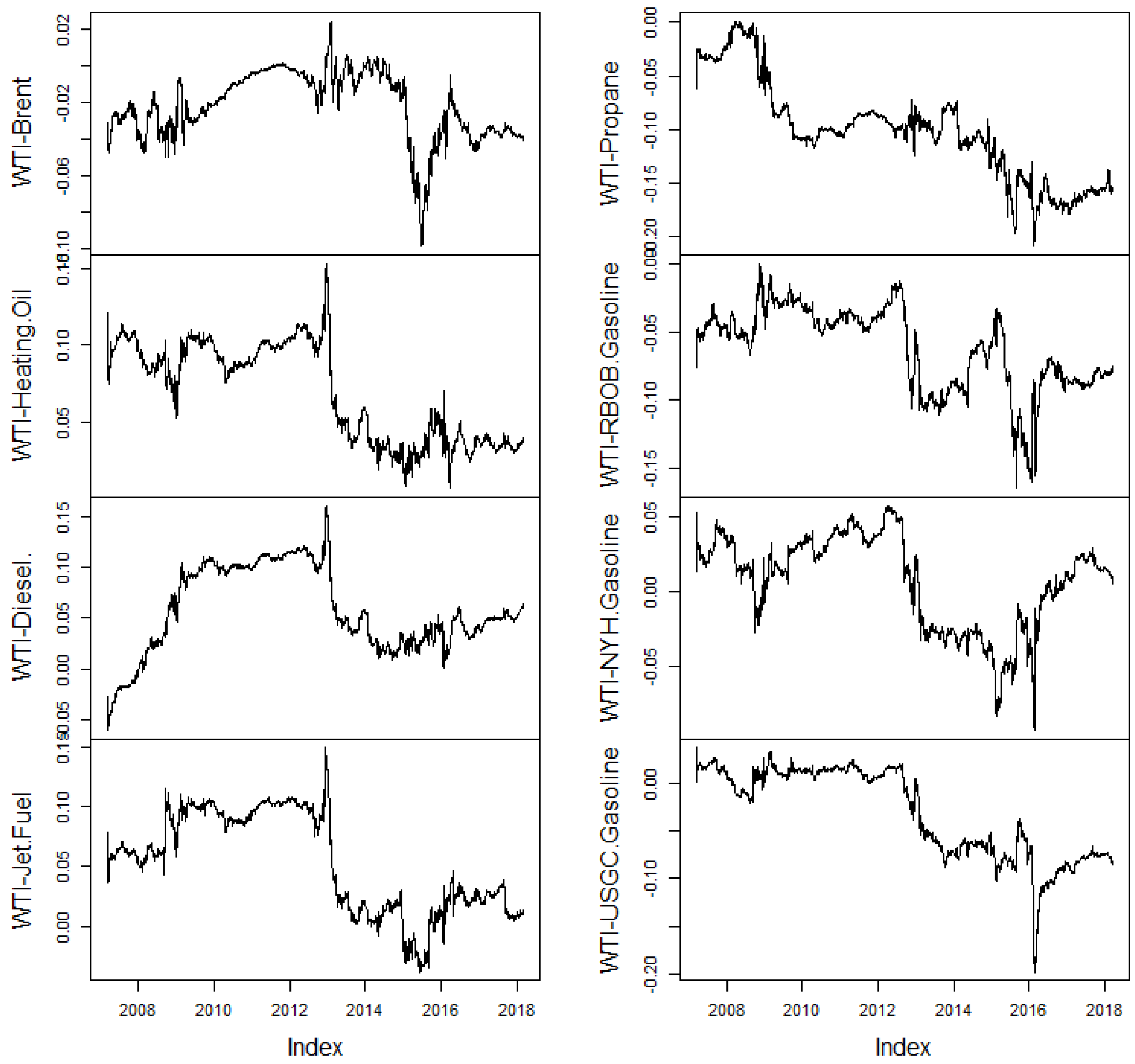


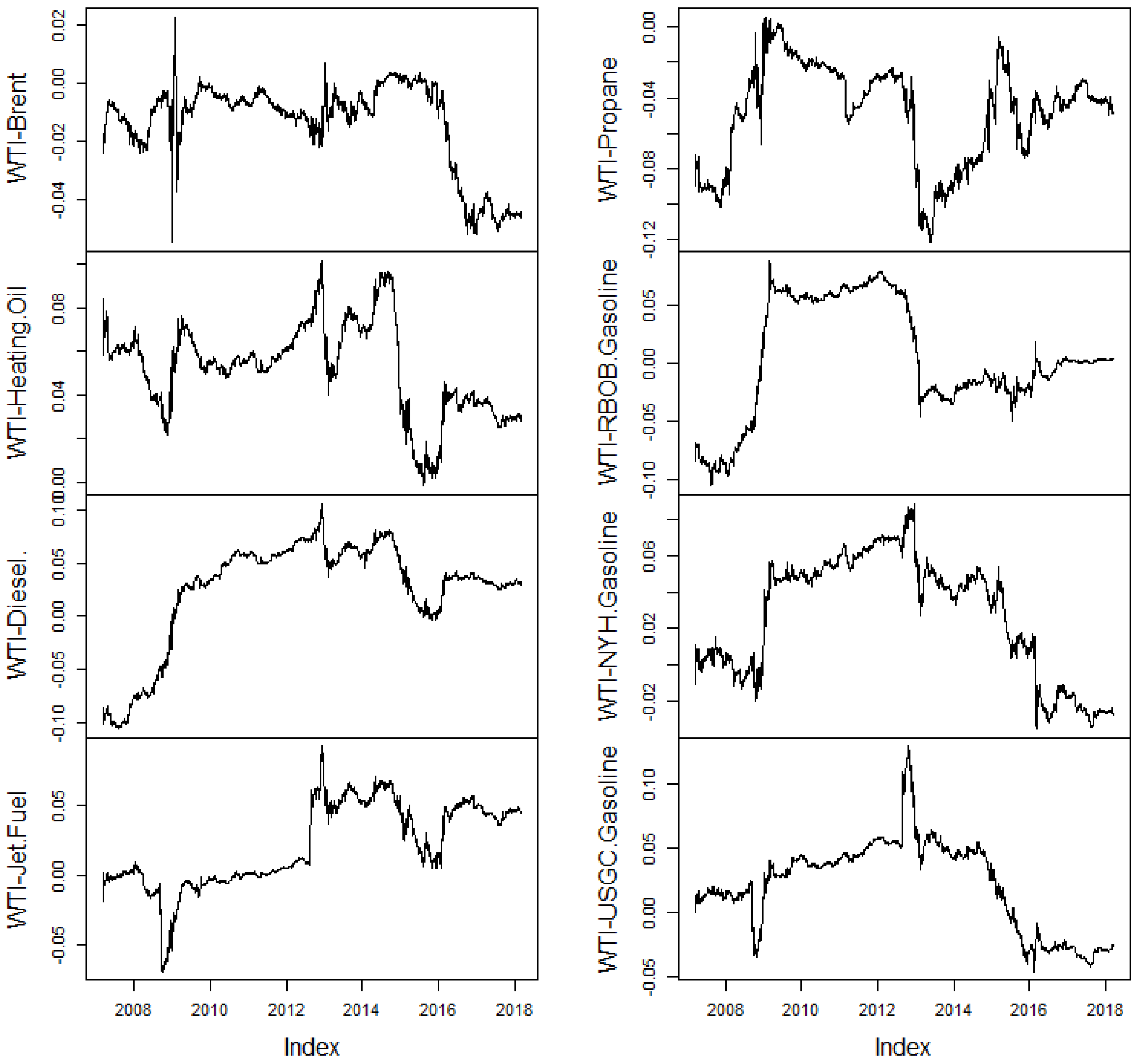
Figure D4: BK Pairwise spillover among considered series



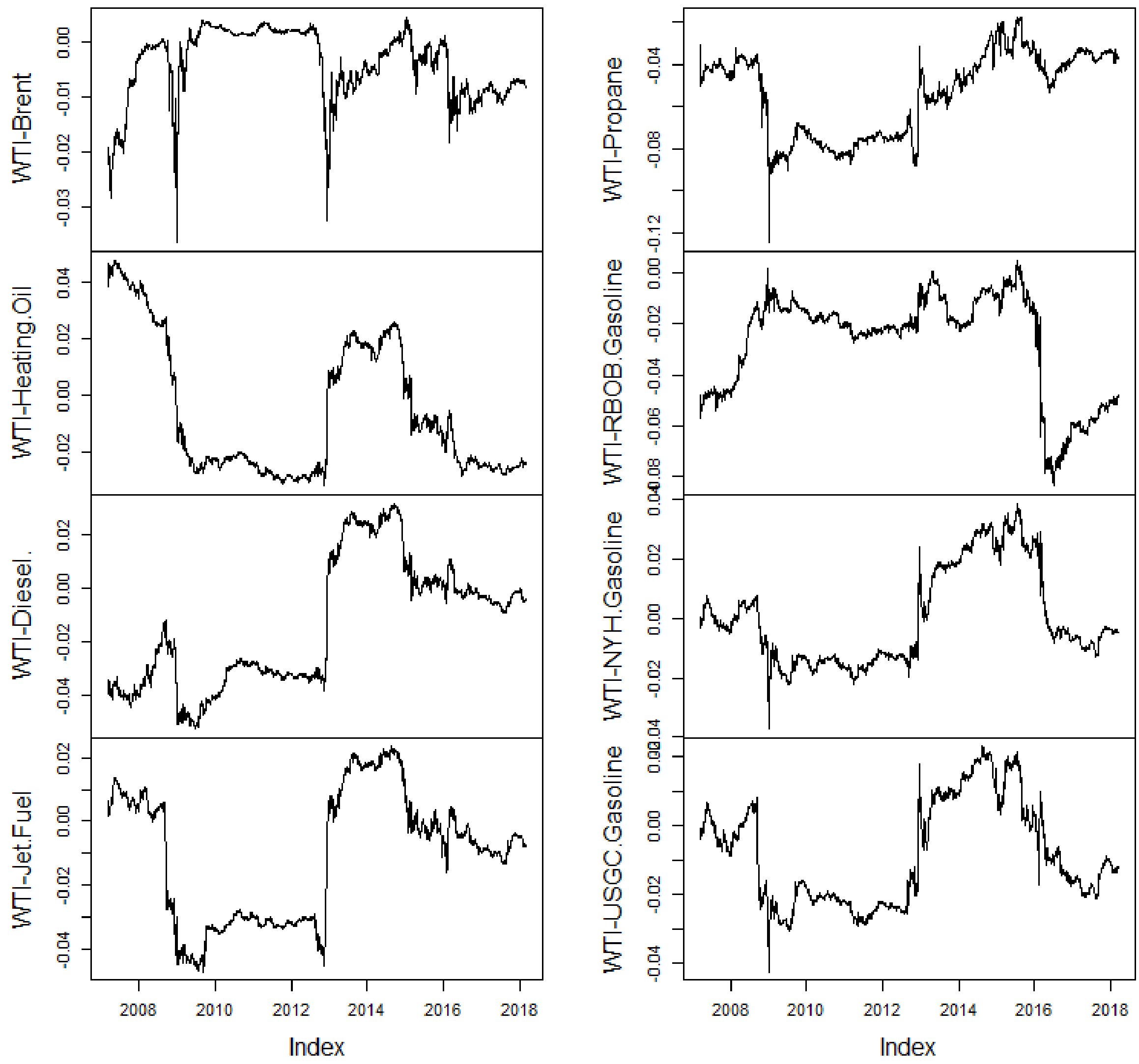
Pairwise spillovers on band: 1.57 to 0.79.



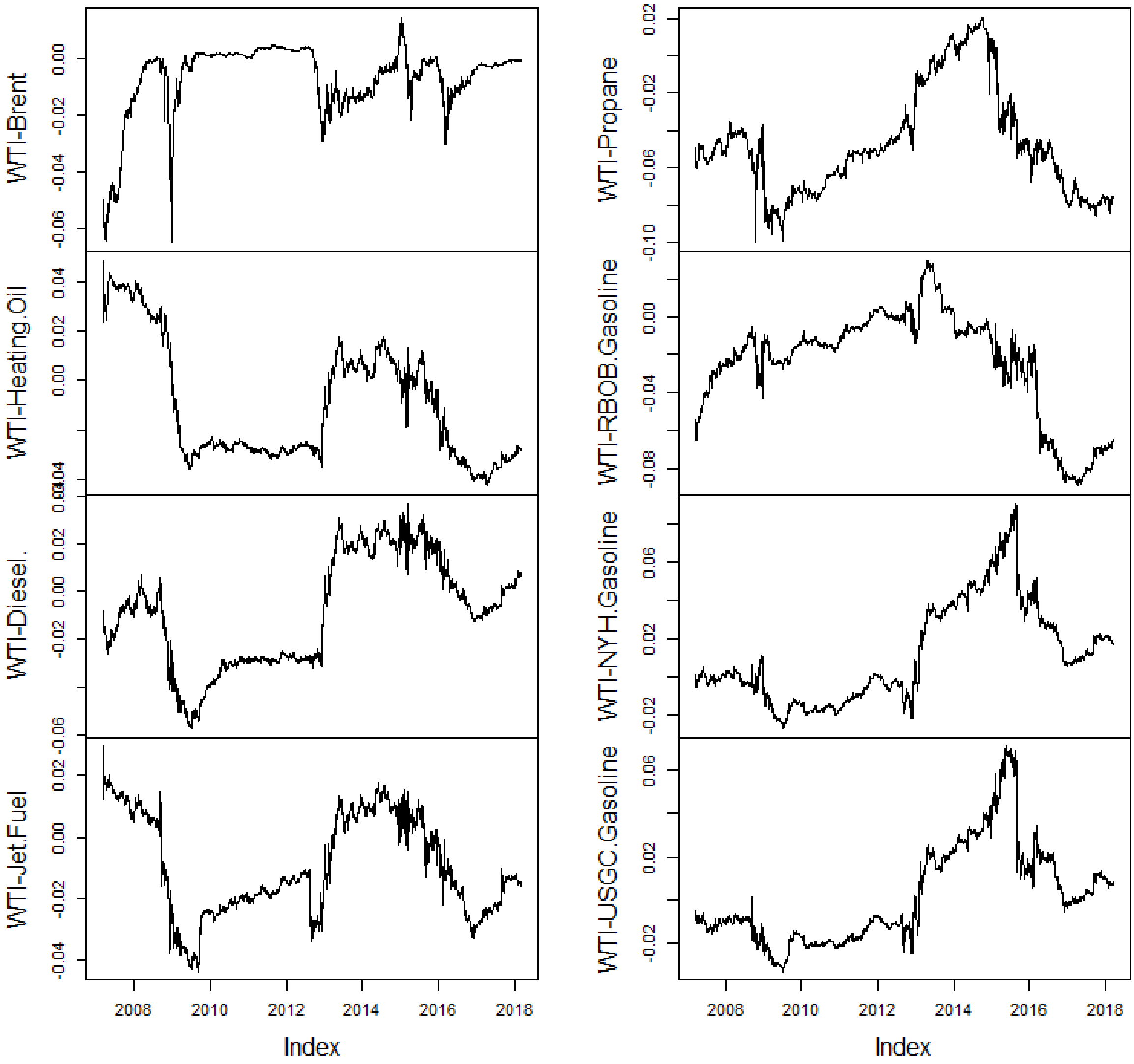
Pairwise spillovers on band: 0.79 to 0.39.



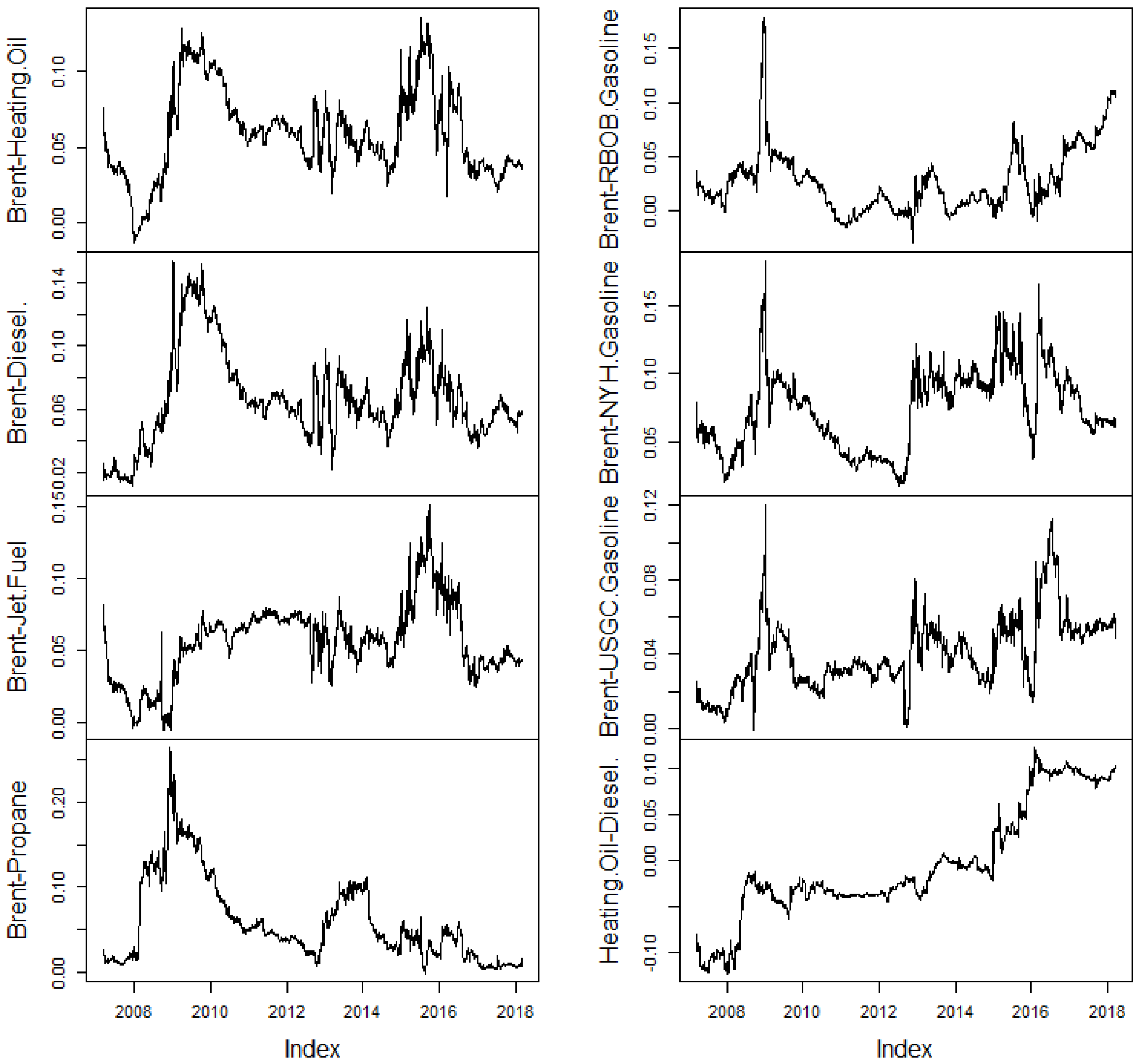
Pairwise spillovers on band: 0.39 to 0.20.



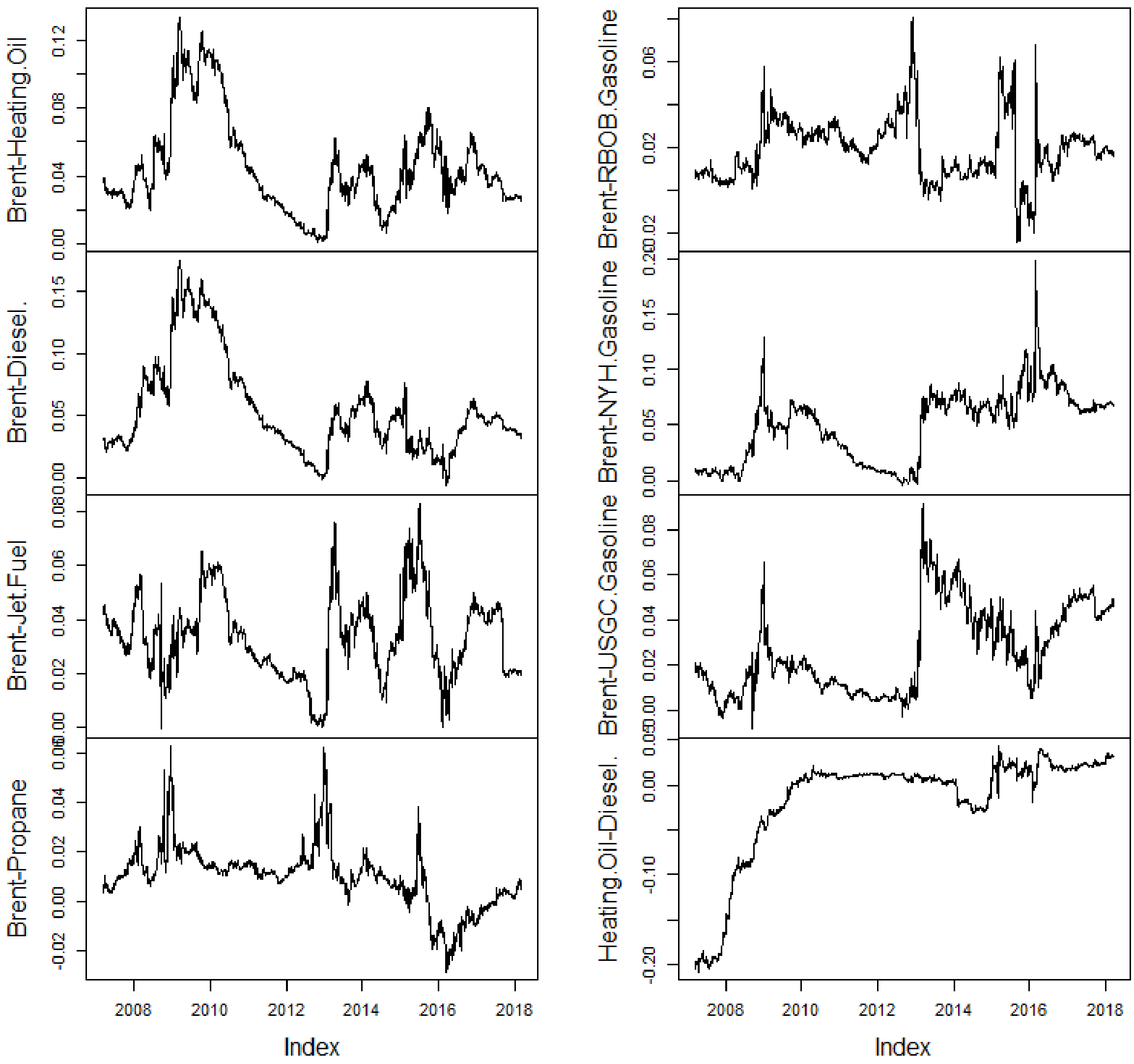
Pairwise spillovers on band: 0.20 to 0.00.



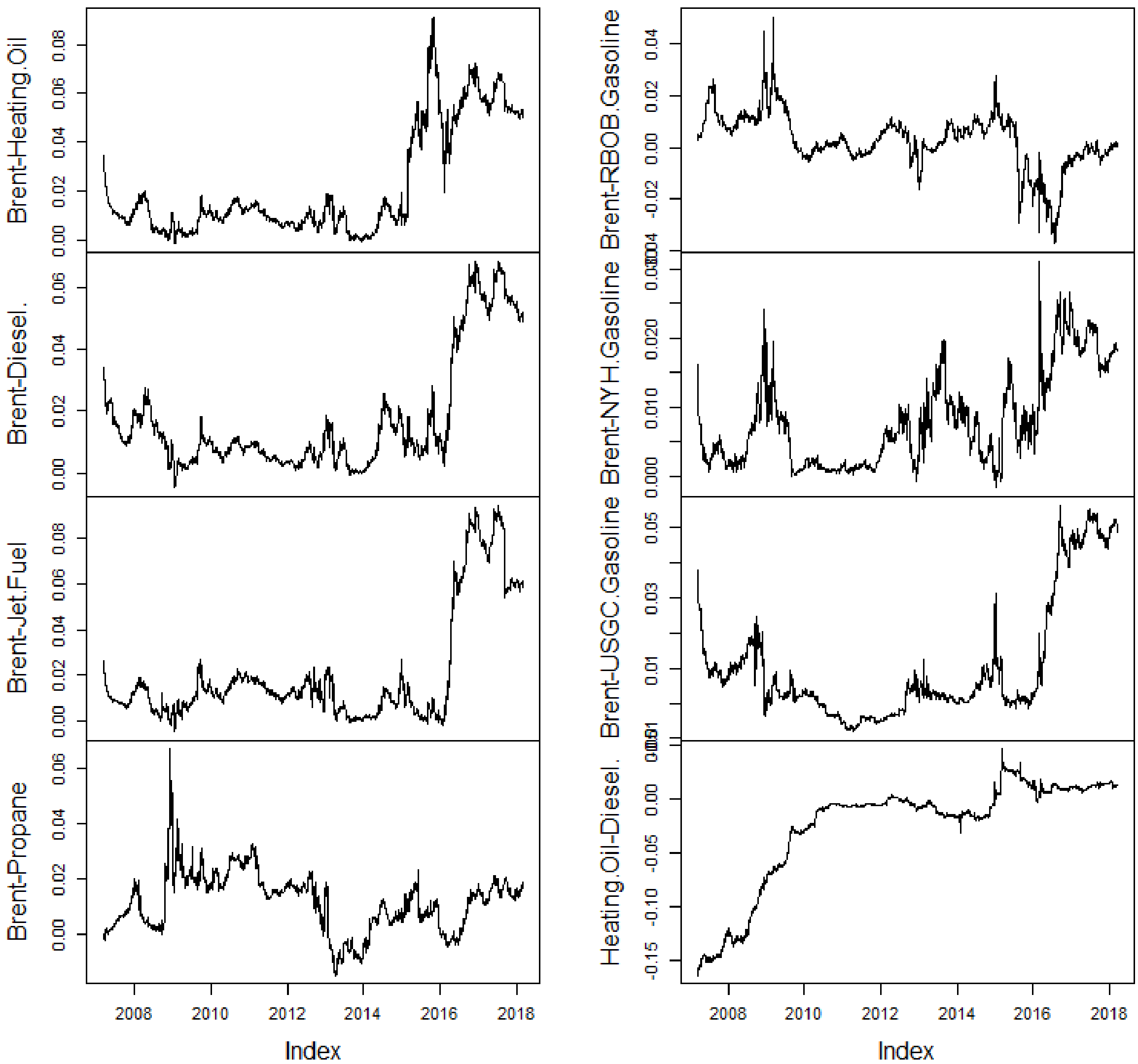
Pairwise spillovers on band: 3.14 to 1.57.



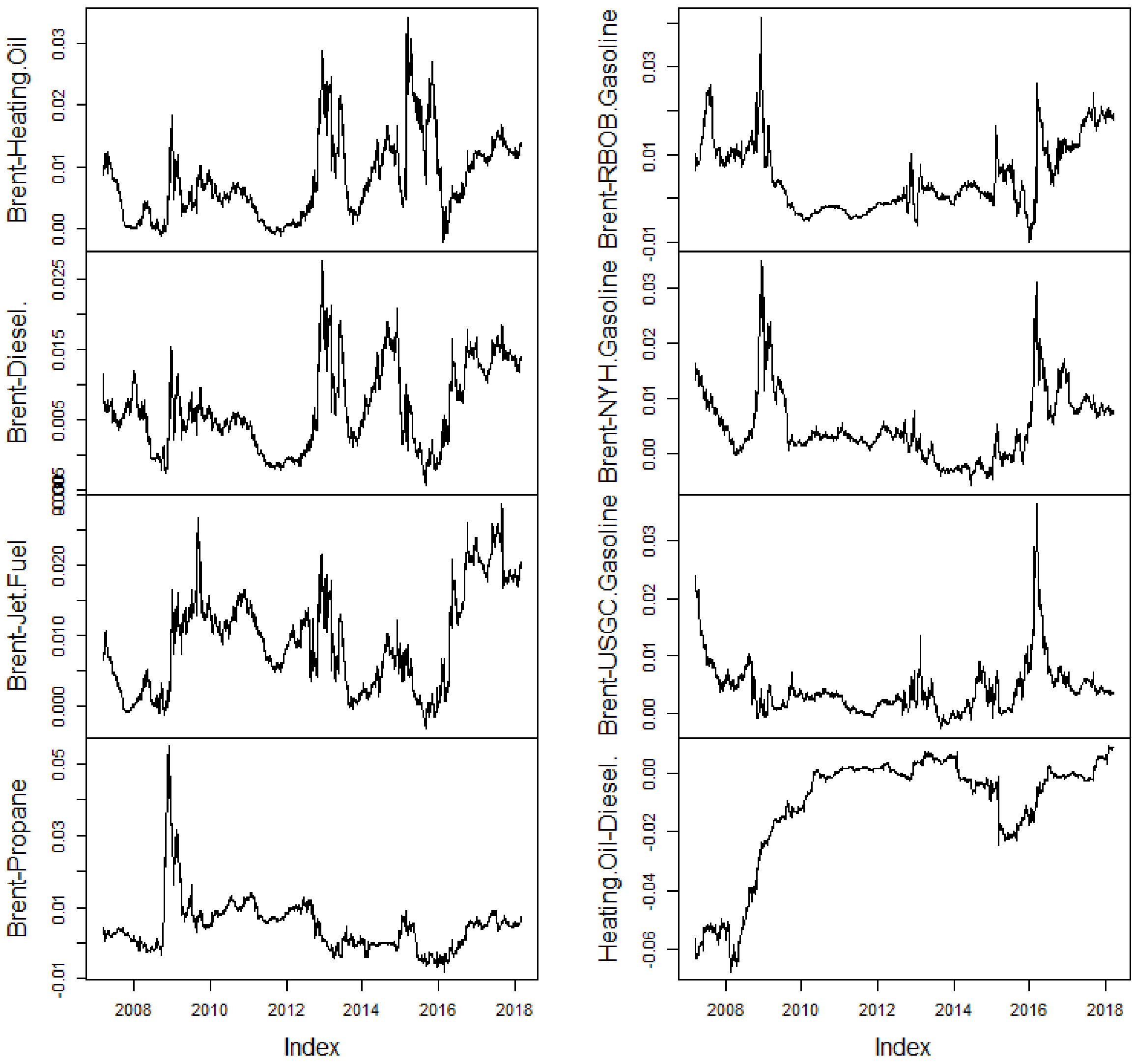
Pairwise spillovers on band: 1.57 to 0.79.



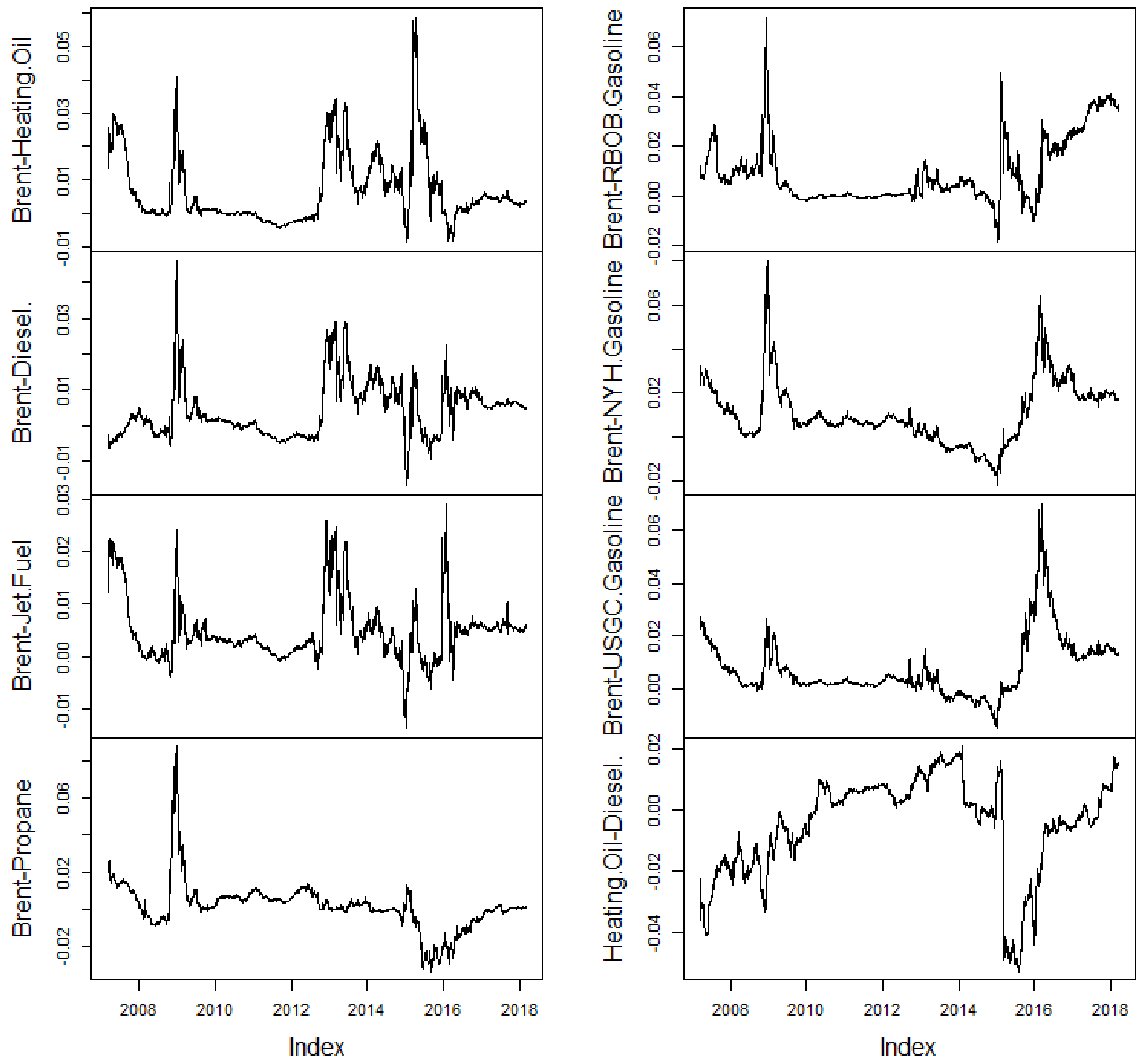
Pairwise spillovers on band: 0.79 to 0.39.



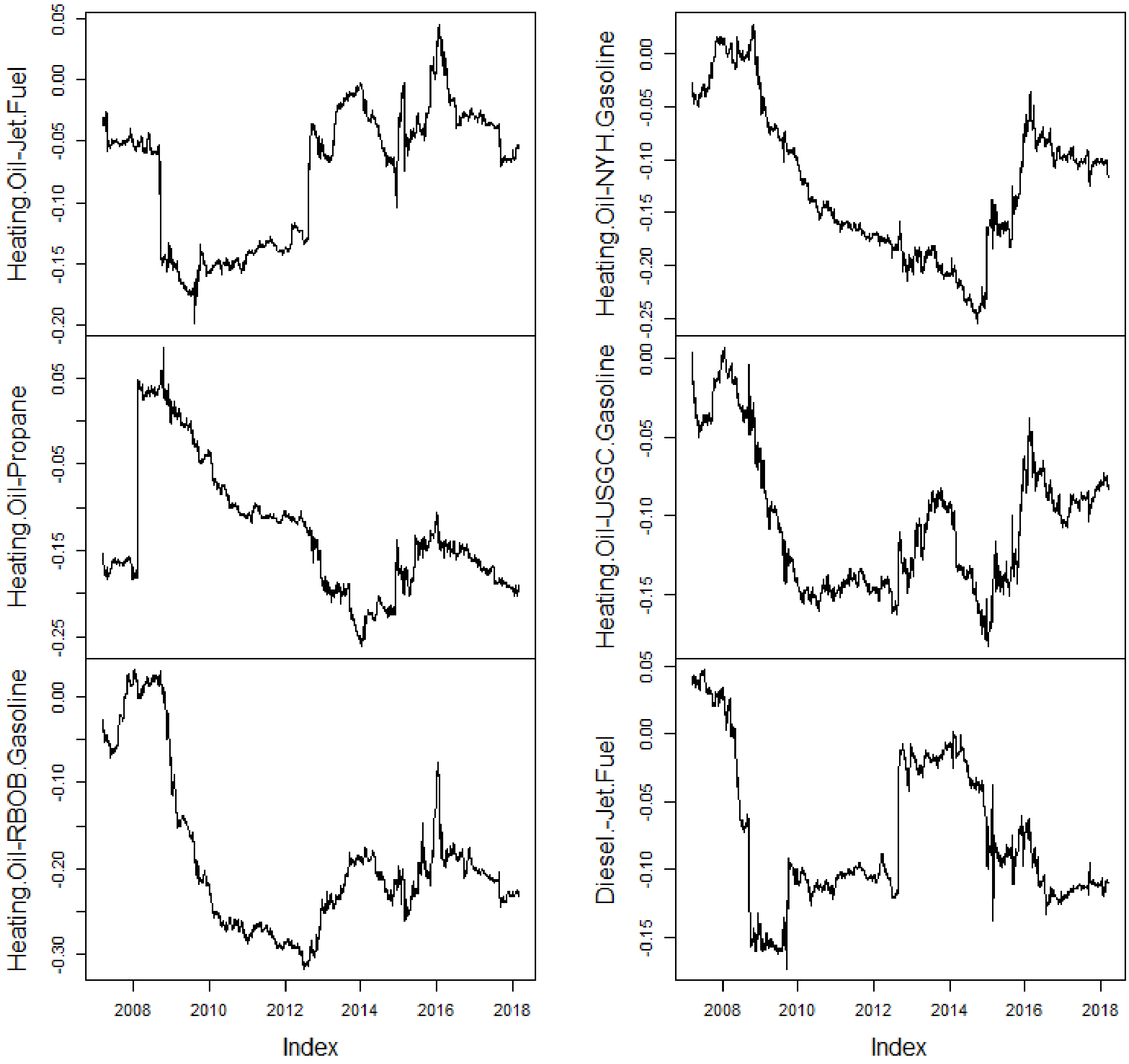
Pairwise spillovers on band: 0.39 to 0.20.



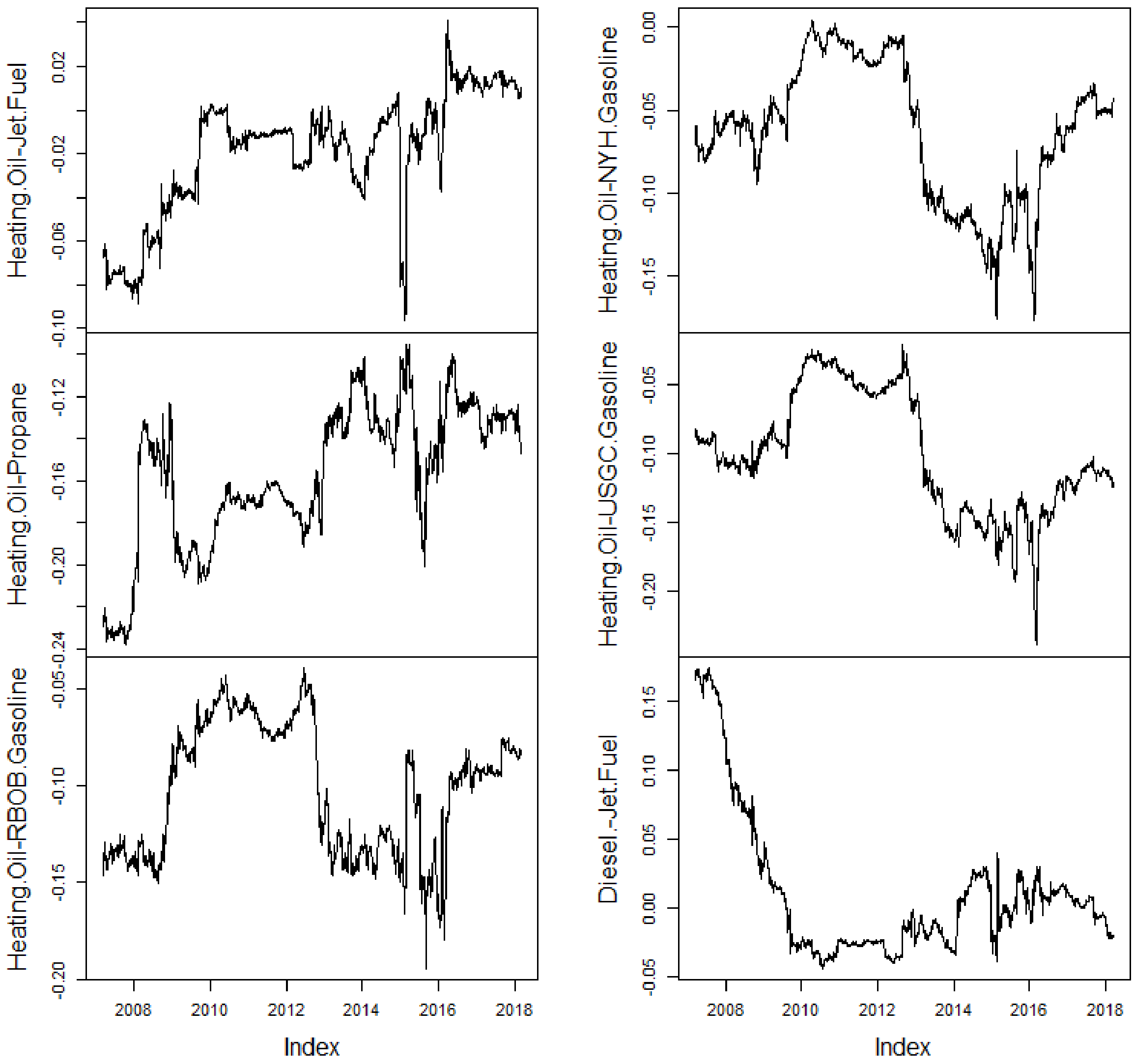
Pairwise spillovers on band: 0.20 to 0.00.



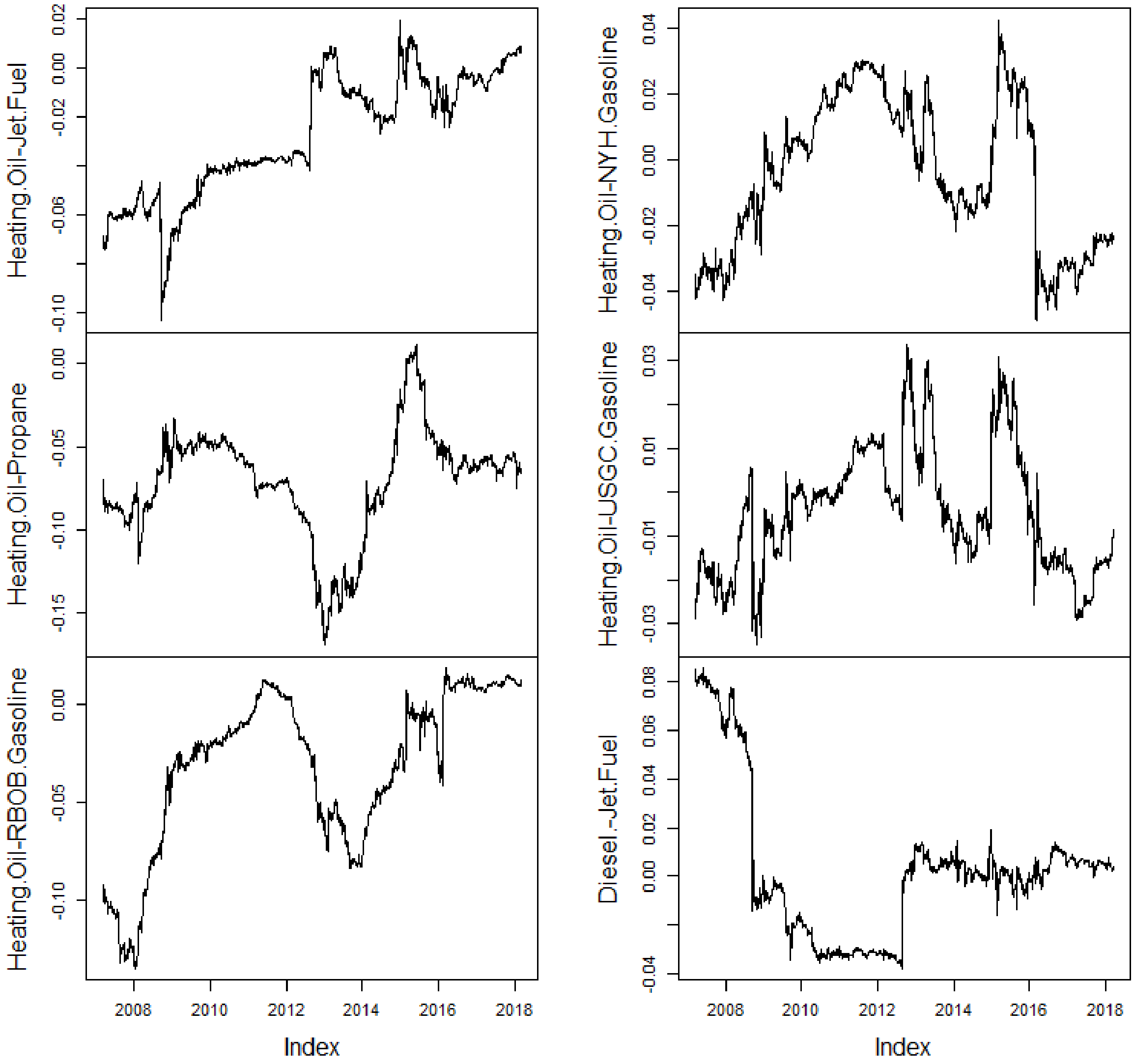
Pairwise spillovers on band: 3.14 to 1.57.



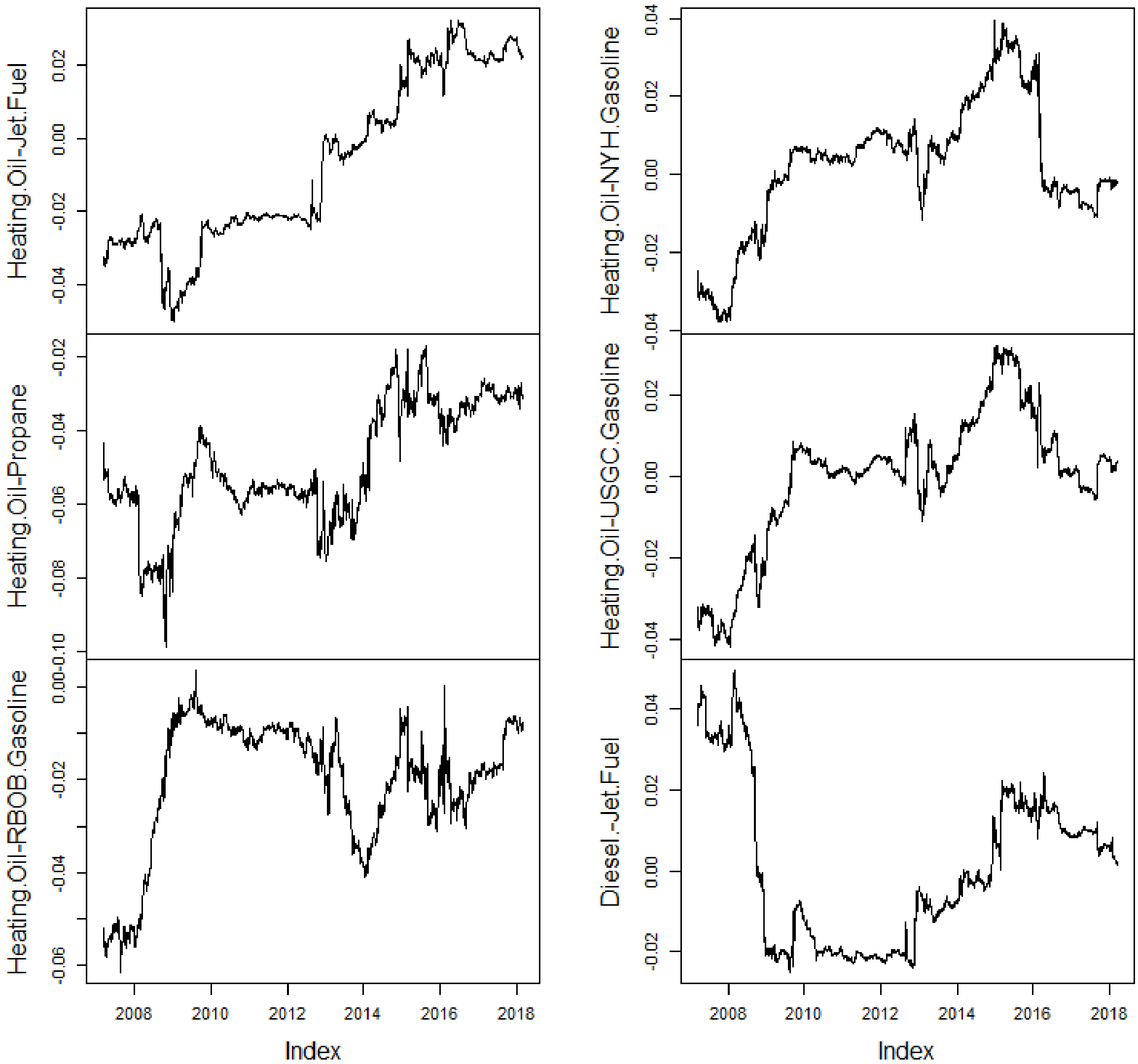
Pairwise spillovers on band: 1.57 to 0.79.



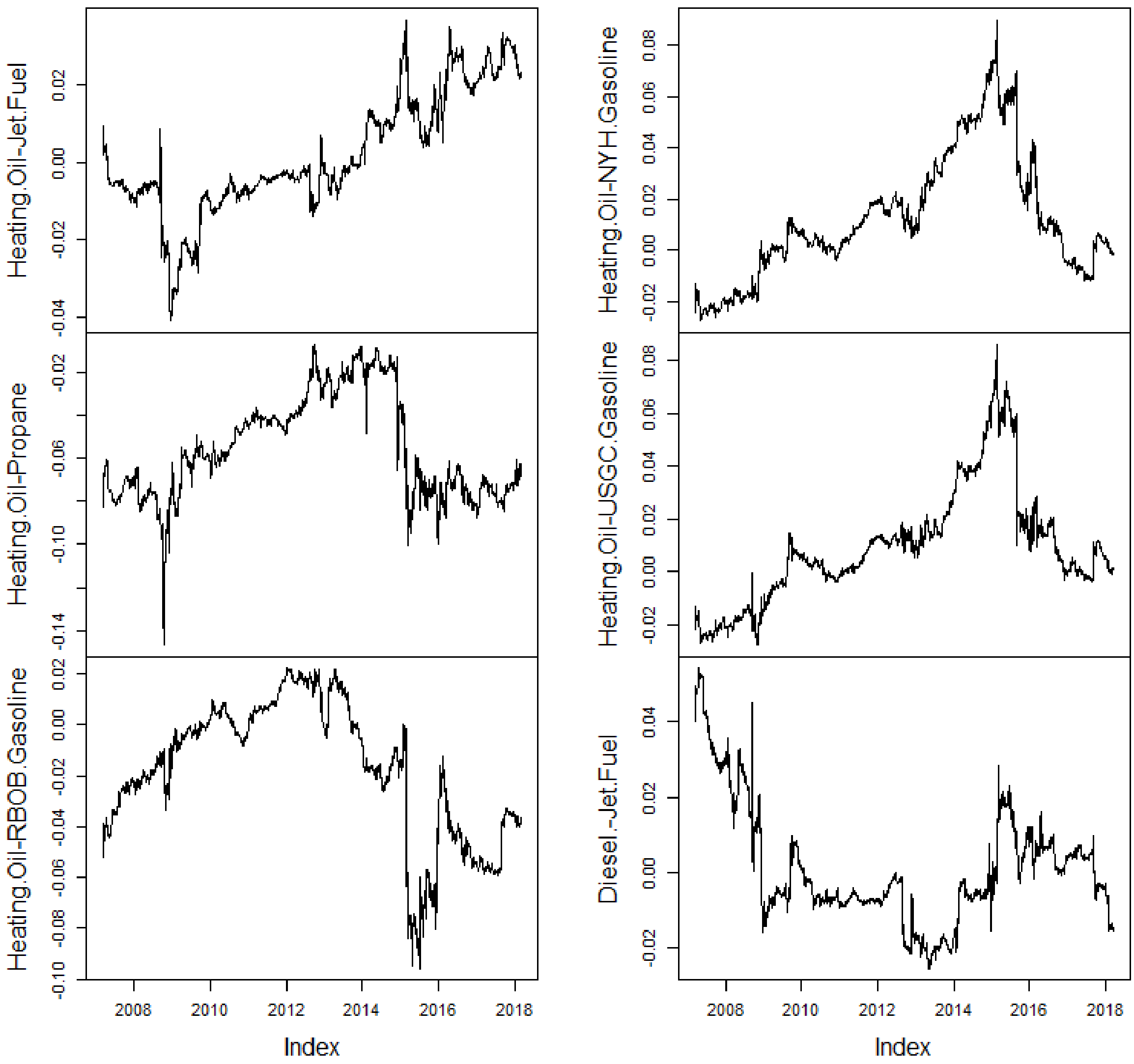
Pairwise spillovers on band: 0.79 to 0.39.



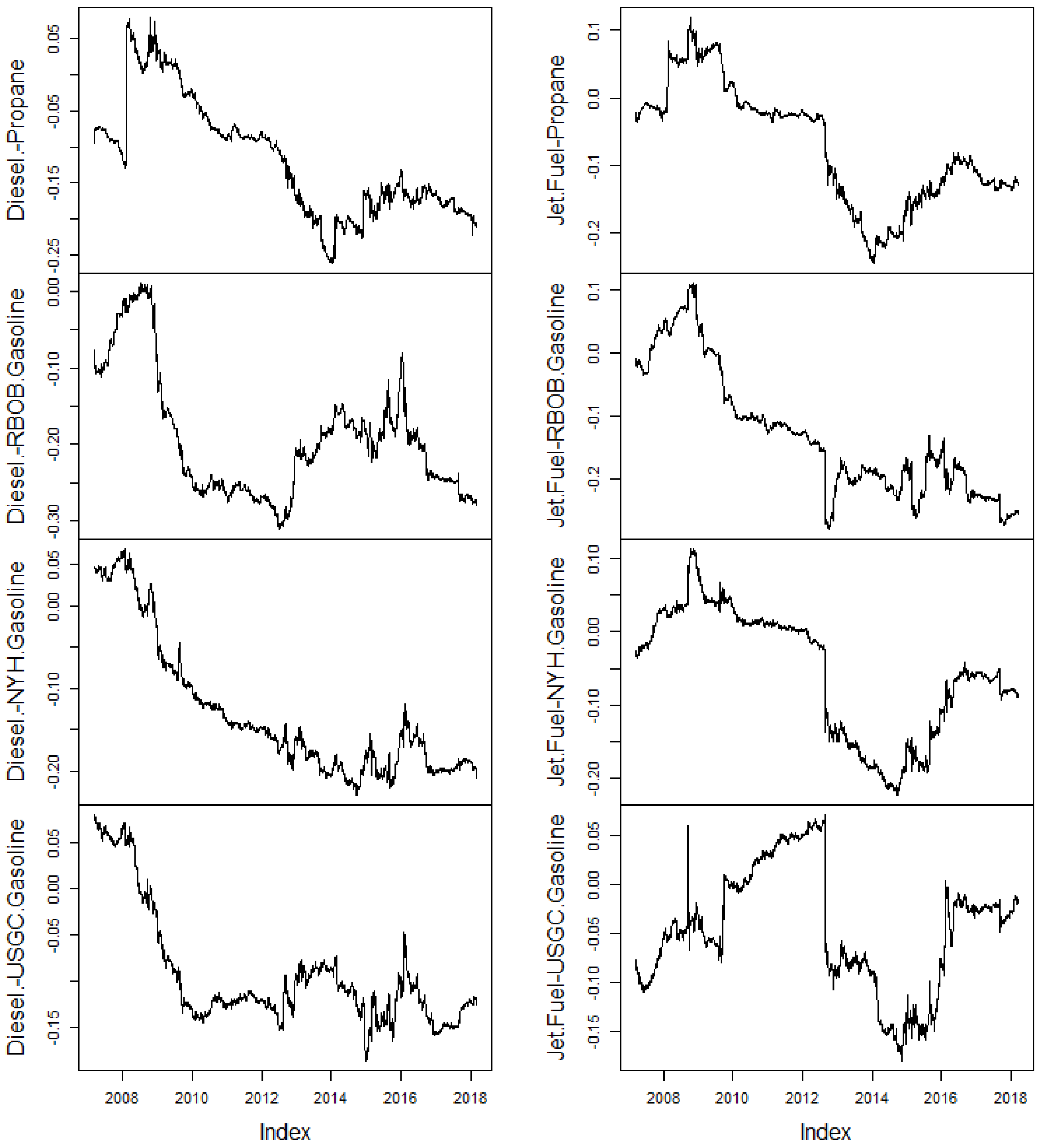
Pairwise spillovers on band: 0.39 to 0.20.



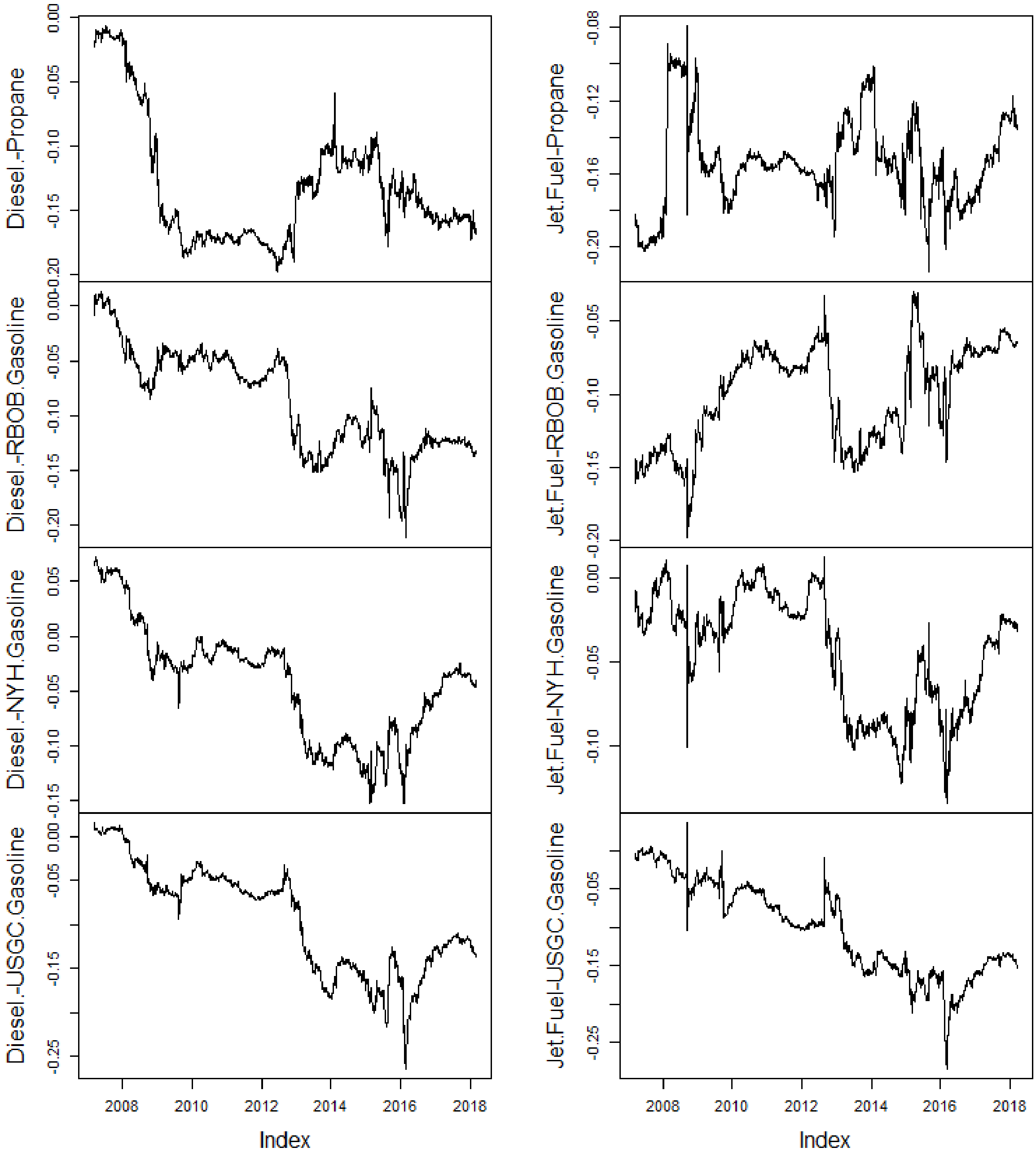
Pairwise spillovers on band: 0.20 to 0.00.



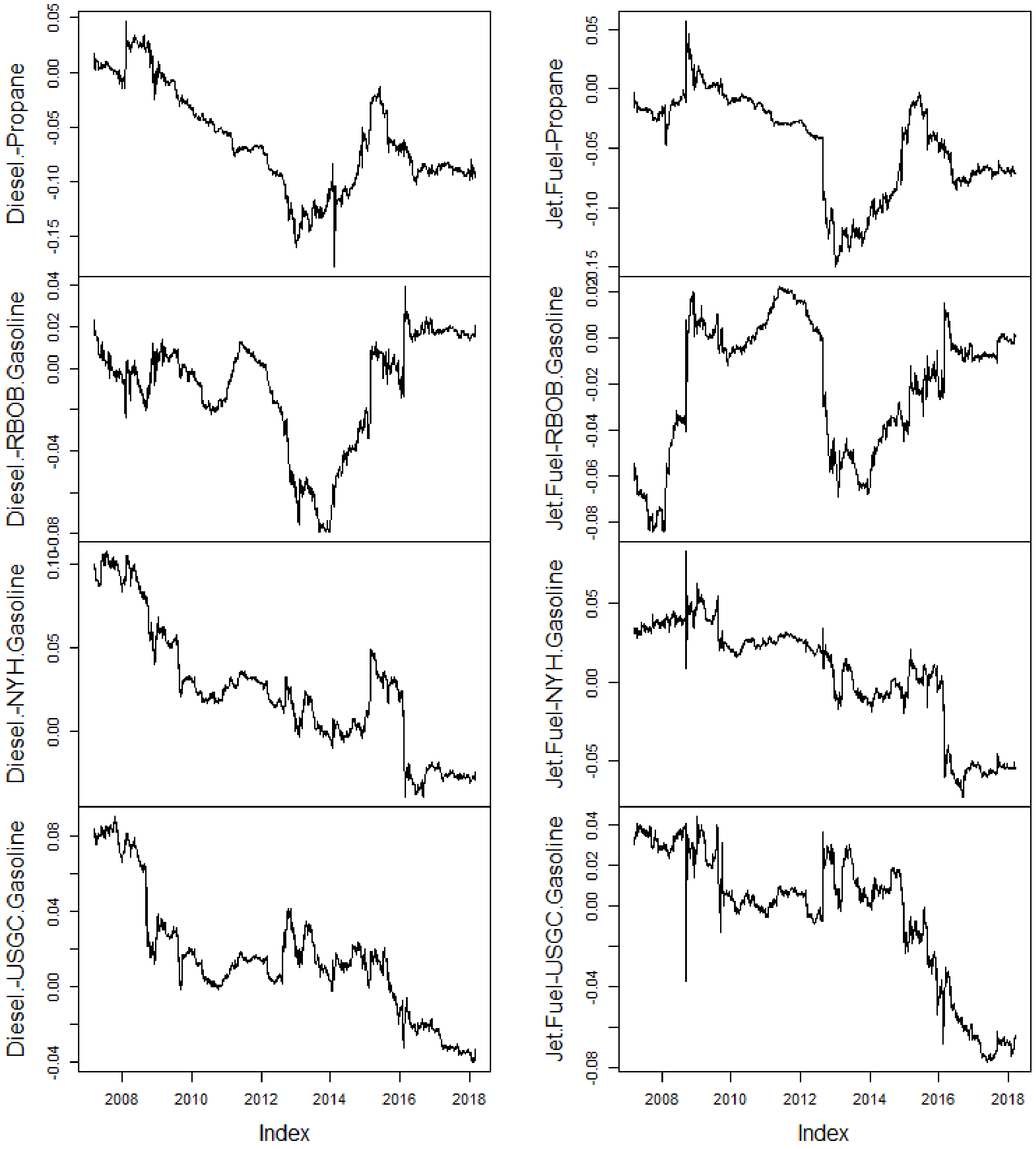
Pairwise spillovers on band: 3.14 to 1.57.



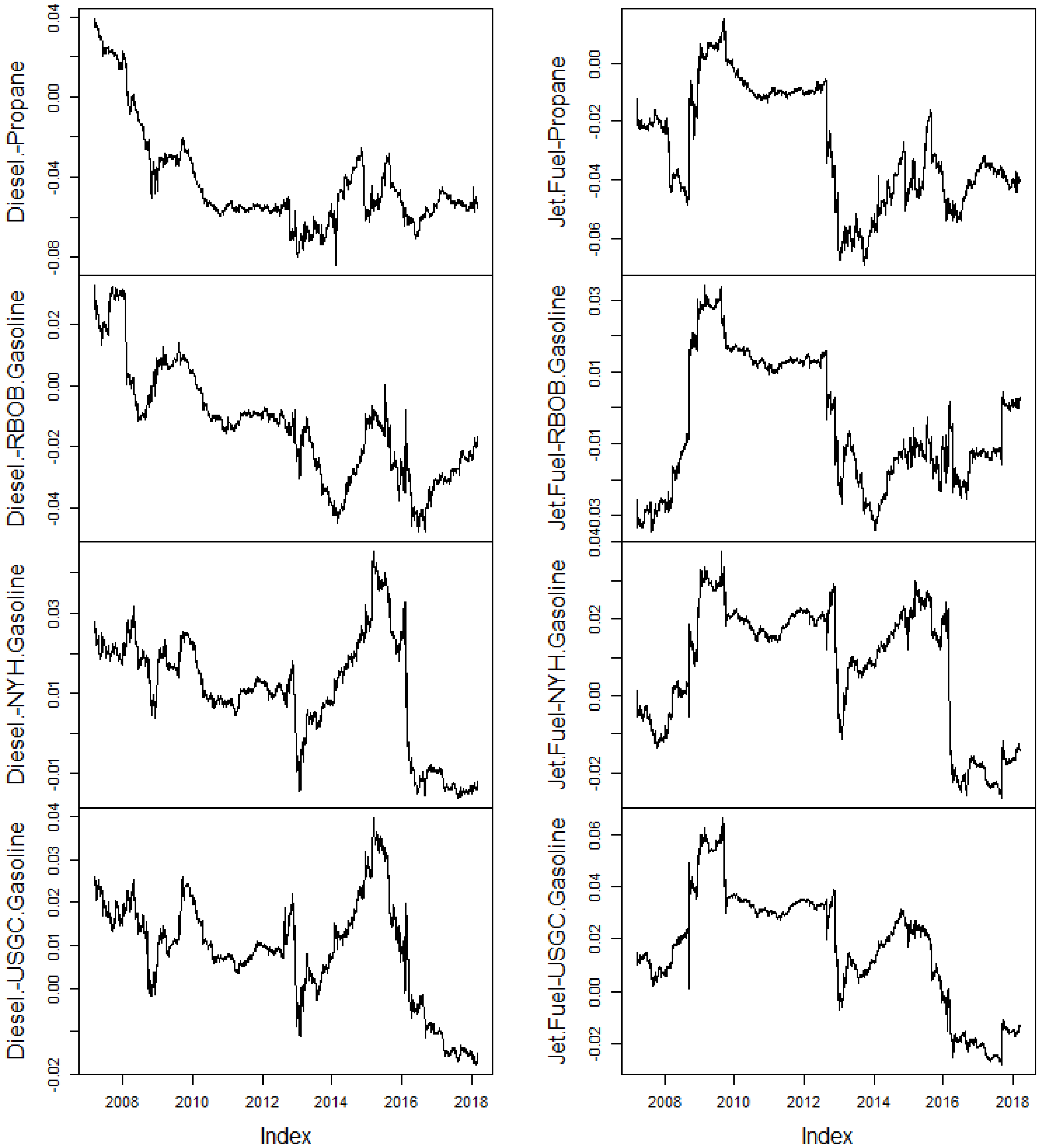
Pairwise spillovers on band: 1.57 to 0.79.



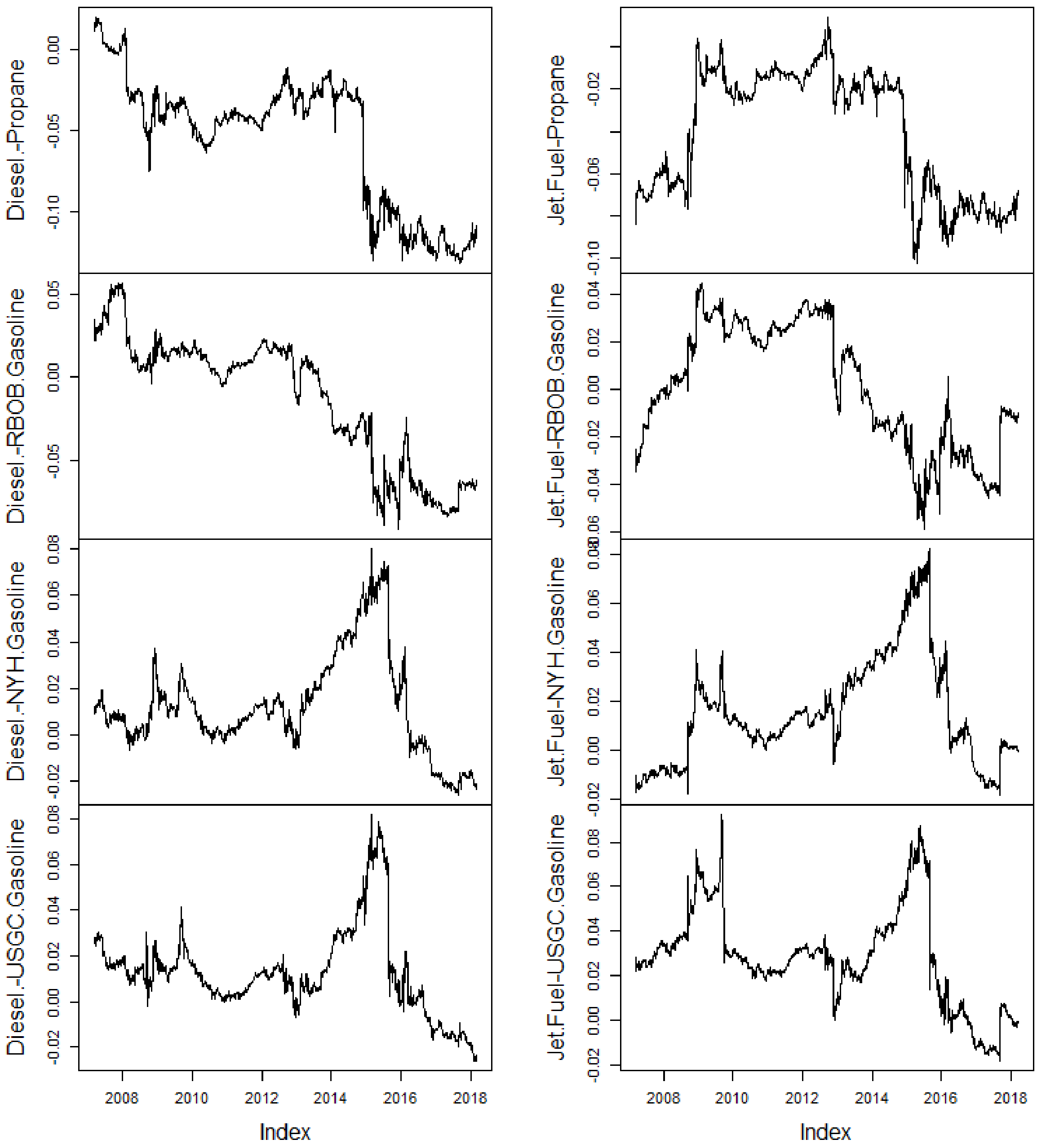
Pairwise spillovers on band: 0.79 to 0.39.



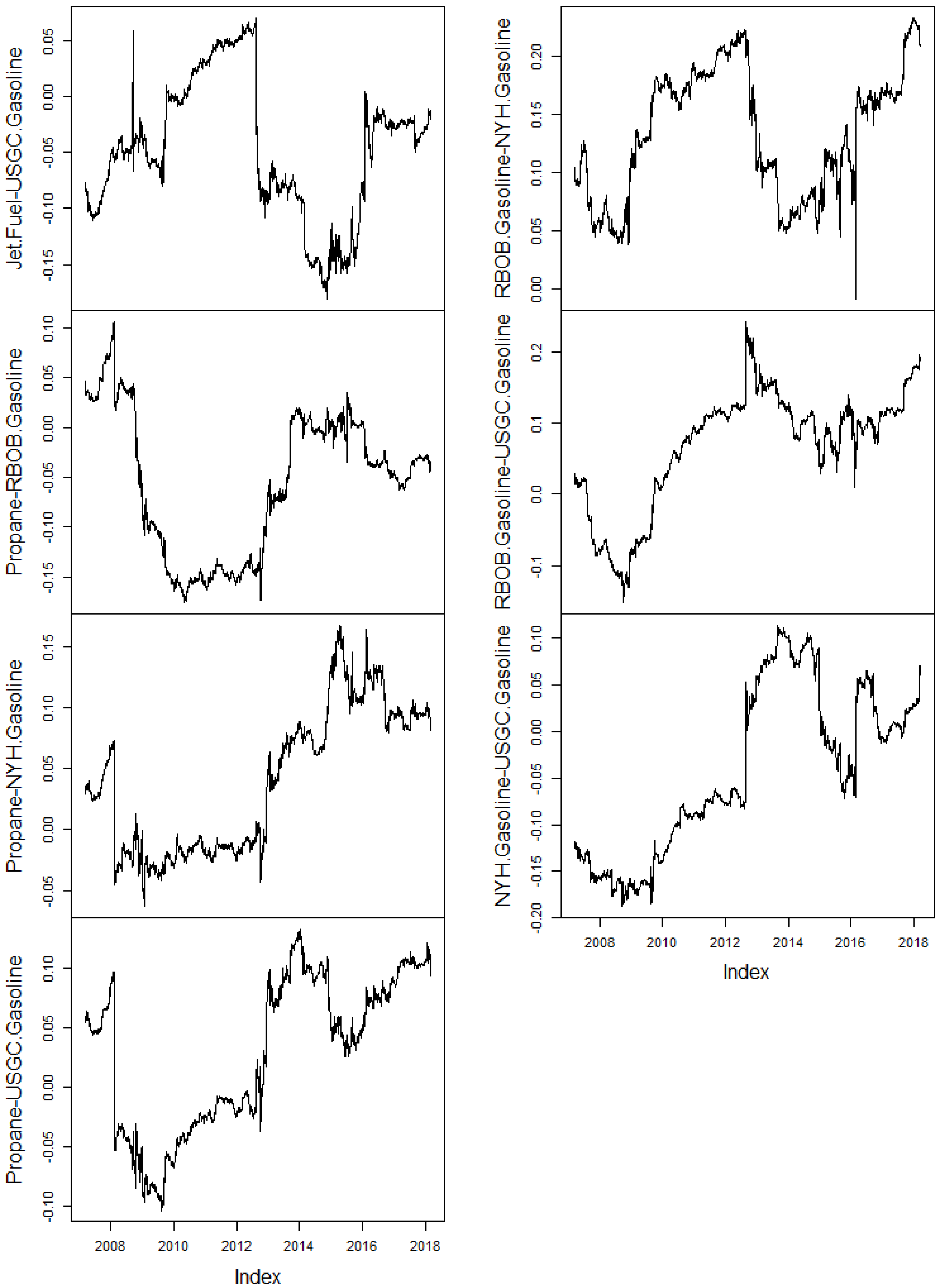
Pairwise spillovers on band: 0.39 to 0.20.



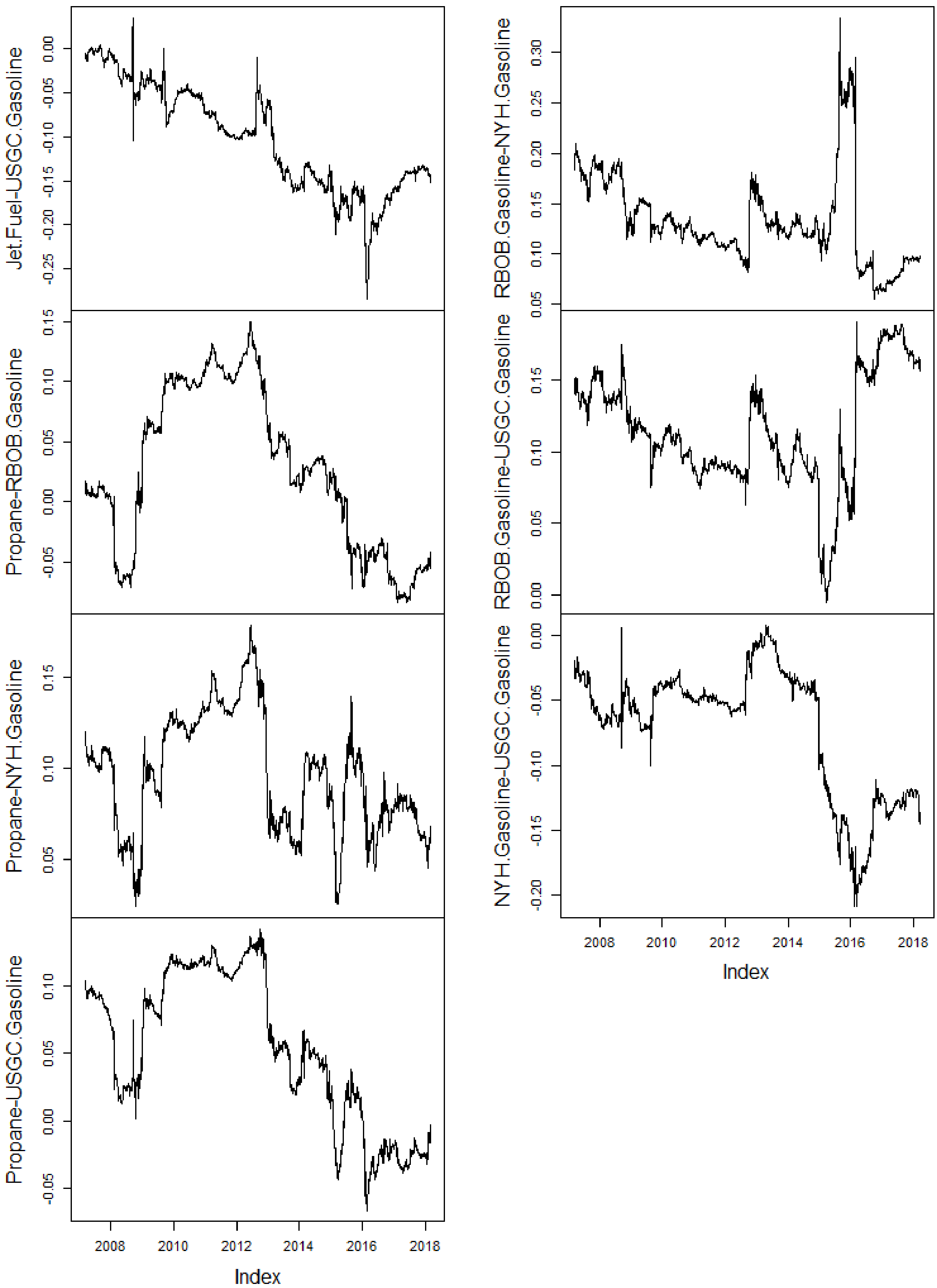
Pairwise spillovers on band: 0.20 to 0.00.



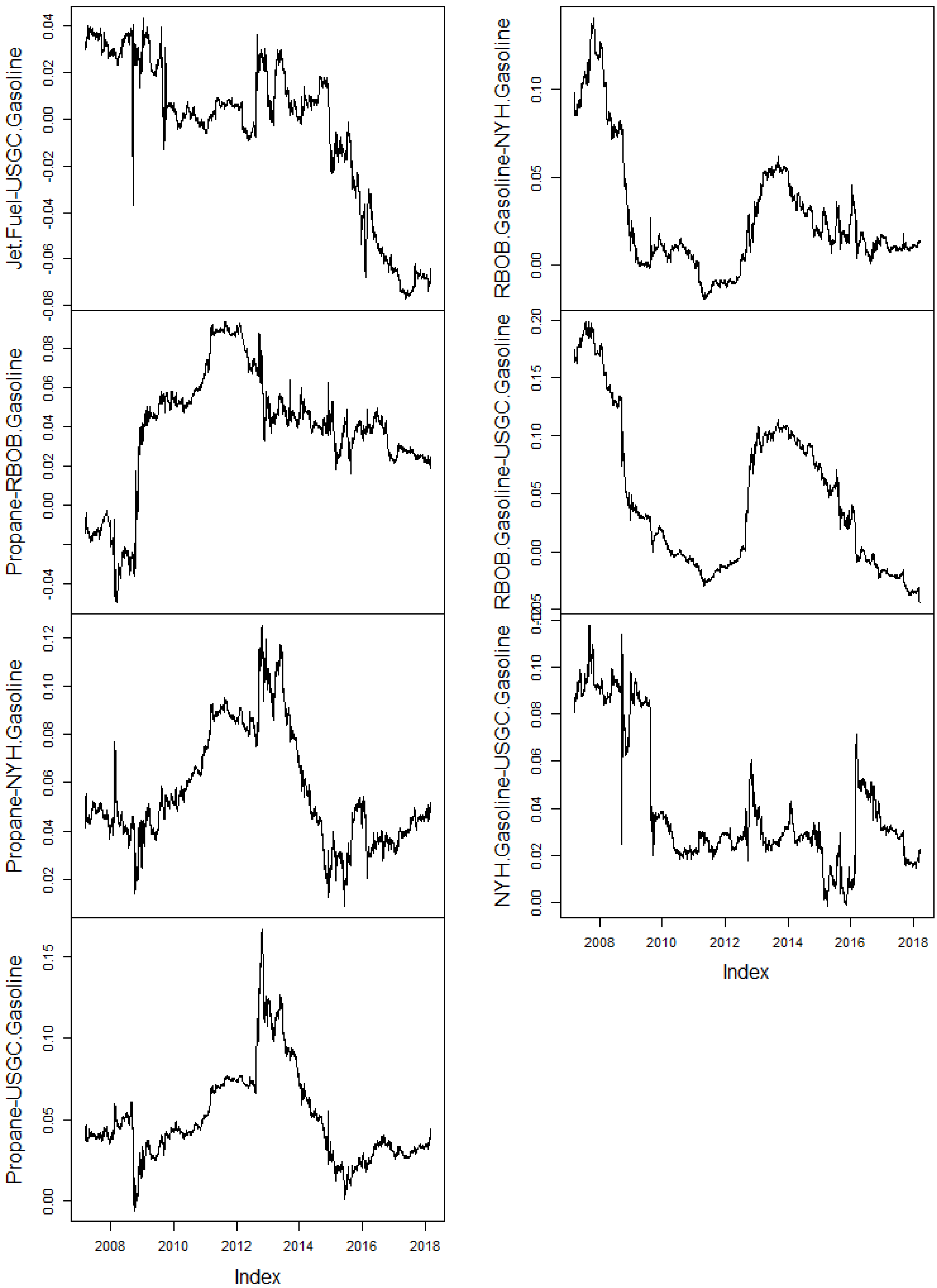
Pairwise spillovers on band: 3.14 to 1.57.



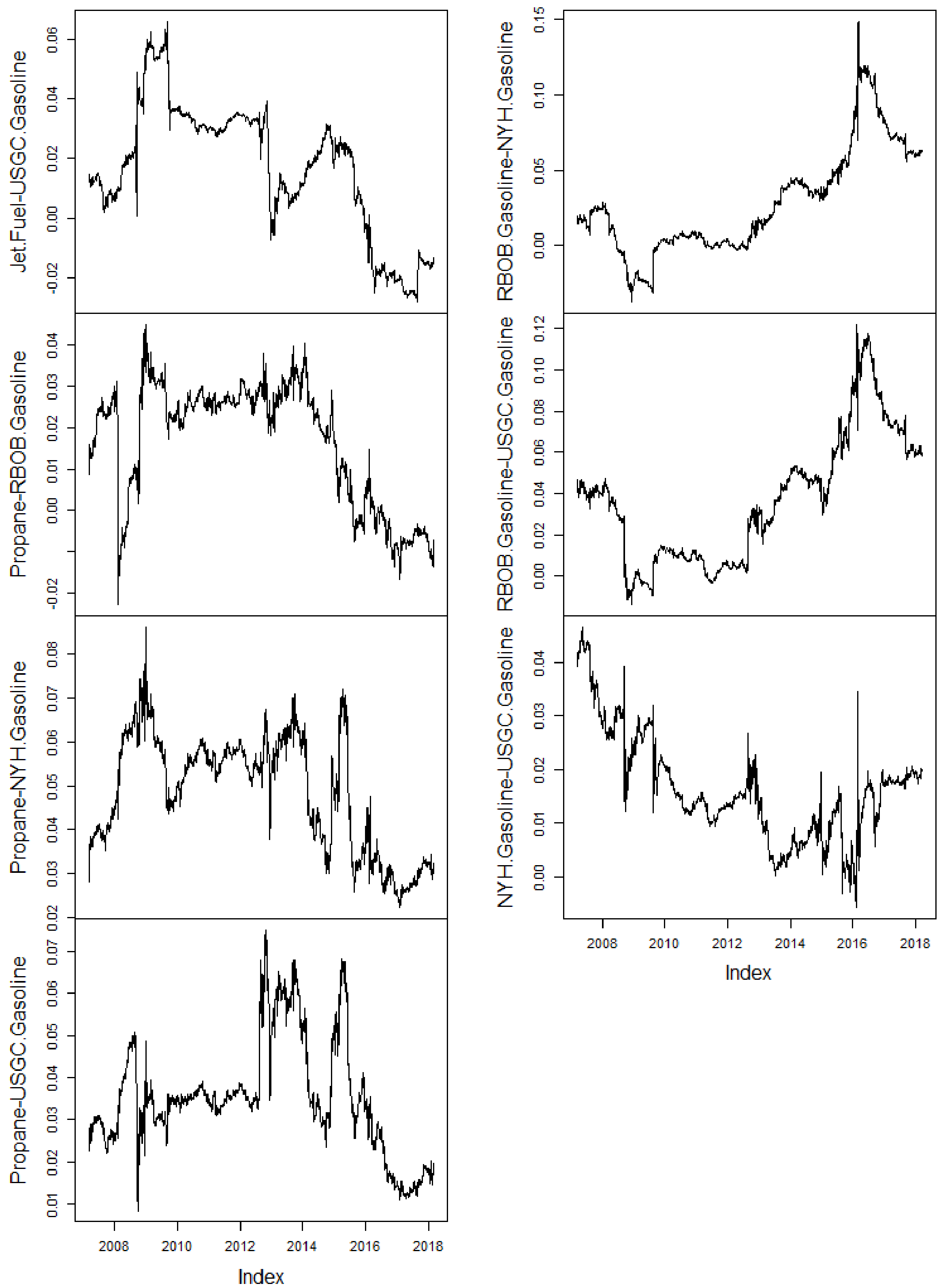
Pairwise spillovers on band: 1.57 to 0.79.



Pairwise spillovers on band: 0.79 to 0.39.



Pairwise spillovers on band: 0.39 to 0.20.



Pairwise spillovers on band: 0.20 to 0.00.