Impact of Shale Revolution on Oil and Natural Gas Prices*

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Abstract

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1 Introduction

An important innovation in the energy industry over the past two decades is the combined use of horizontal drilling and hydraulic fracturing techniques, which allows producers to extract oil and gas from low permeability reservoirs in a cost-effective manner. Although neither of these techniques is new, a long history of private and government investment led to producers in the Barnett area to combine them in an economically feasible manner. This has triggered a major increase in the unconventional oil and gas production in the United Statesbetween 2008 and 2019, the total natural gas and oil produced in the U.S. increased more than XXX and XXX, respectively (EIA, XXXX). The rise of shale oil and shale gas has reversed the decade-long declining trend in U.S. oil production, and made the U.S. on track to become a big player in the global liquefied natural gas trading. Over the past several years, U.S. has surpassed Saudi Arabia and Russia as the top oil producer in the world, as well as become the worlds largest producer of natural gas (EIA, XXXX).

The shale boom is often cited as a major contributor to the sustained low natural gas prices in the U.S., and to a less extent, depressed global oil prices in recent years. For instance, Wiggins and Etienne (2017) show that the projected natural gas prices in the U.S. with only supply shocks after 2012, most of which are related to shale production, aligns closely with the actual natural gas price behavior. Baumeister and Kilian (2016) estimated that as much as \$16 of the \$46 cumulative decline in the Brent oil prices in the second half of 2014 could be attributed to positive supply shocks, including the rising shale oil production in the U.S. and supply responses in other countries.

An alternative view is that the technological innovation and investment in the energy sector were driven primarily by its high-profit margin, in particular prior to the 2008 financial crisis when oil and natural gas prices hit record highs. These high prices had made the shale technology cost-competitive when it was first introduced, stimulating further investment that led to massive productivity gains and lowered the cost of production. Kellogg (2011), for instance, uses a dynamic model to show that the oil companys investment behavior responds negatively to changes in uncertainty. The theoretical prediction of his model is supported by the oil drilling behavior in Texas, which increased when the expected uncertainty rose and decreased vice versa. Such theory is very important because the oil and gas industry has relatively high sunken cost or the irreversible investmentthe producers have to invest upon the uncertainty of finding and extracting reserves that vary considerably in terms of geographical variation, types of rocks to be drilled, depth of reserves and the price volatilities. Kellogg (2014) finds: the empirical estimates that are consistent with theoretical prediction of the responses of drilling activities with respect to price volatility; a significant response of cost of failing to respond with volatility shock; and implied volatility data derived from futures options prices yields a better fit to firms investment behavior than backward-looking volatility measures such as GARCH.

In this paper we investigate the relationship between exploration/investment activities and energy prices, focusing on oil and natural gas industries in the United States during the shale boom. Although various measures exist for oil and gas exploration and development (e.g., number of wells drilled, investment spending, etc.), these data are not publicly available and often only exist for a shorter time period. We hence follow the literature (Khalifa et al., 2017; Ringlund et al., 2008) and use rig activities as a measure of exploration effort and field development that took place in the oil and gas industry.

According to the EIA, a rig is "a machine used for drilling wells that employ a rotating tube attached to a bit for boring holes through rock," and rig counts refer to the number of "rigs drilling for crude oil, rigs drilling for natural gas, and other rigs drilling for miscellaneous purposes." In general, as rigs are used for drilling new wells to explore for or develop/produce oil and gas, the rig count provides information on oil and gas companies' willingness to continue investing in the industry, which should rise when energy prices (or profit margins) are high and vice versa. Additionally, as rig counts indicate the actual activities carried out by oil and gas companies, they are often considered the barometer of the performance and health of the energy industry, as well as the degree of investor confidence and the level of future energy output. The rig counts data are periodically published by EIA, along with prices and various other supply and demand information to better inform market participants. The importance of rig count is clearly explained by Baker Hughes, who has been reporting rig count data for over 70 years:

> "Baker Hughes Rig Counts are published by major newspapers and trade publications, are referred to frequently by journalists, economists, security analysts and government officials, and are included in many industry statistical reports."

A number of papers have analyzed the relationship between rig counts and oil prices. Khalifa et al. (2017) concludes that the relationship between oil prices and rig counts, and consequently the oil supply can be categorized into three dimensions: 1) the change of drilling speed and productivity over the business cycles; 2) how exploration and investment activities in the oil industry respond to different economic conditions; and 3) how oil price changes affect rig activities. Of the first strand of the literature, the existing papers (Osmundsen et al., 2008, 2010) primarily examines The second strand of literature................The third dimension of the literature analyzes how rig drilling responds to oil price changes,

The present paper extends the last strand of papers, by looking at the information spillover between rig counts and energy prices in the United States, namely crude oil and natural gas, and how these relationships have evolved over time under different market conditions. Although it is generally believed that unconventional oil and gas producers tend to be more price sensitive than conventional oil producers due to a higher marginal cost of production incurred by the former (XXXXXX), Kilian argues that the investment decisions may respond to price fluctuations rather differently. For instance, the investment horizon of unconventional oil and gas is typically much shorter tha and the declining productivity over time of unconventional oil and gas production and. Indeed, Baumeister and Kilian (2016) finds that oil investment spending compared the 2014-16 episode with the large, sustained oil price decline in 1986-87, suggests that oil investment spending has in fact become less responsive to oil price changes during the recent tight oil boom. Examining the information spillover between

Our paper contributes to the present literature in at least three ways. First, despite the work by.Second, unlike previous studies that only focus on the oil industry, the present paper also examines the interactions between rig counts and prices for the natural gas industry , which has surpassed coal as the second-largest energy sector in the US. Since rigs can be employed either for oil or natural gas exploration, the number of active rigs not only indicates the investment activities in these sectors, but also shows the relative strength of investor confidence between the two sectors.

Third, although papers dynamic

The remainder of the paper is organized as follows. In section two we provide a brief theoretical framework that

2 Theoretical Framework

In this section, we provide a simple game theoretic setting on how oil and gas producers behave upon the structural changes led by the shale gas boom in the U.S. and the resulting change in prices and rig count. We start with an oligopoly case in which more than one (but a finite number of) firms compete in the market. Consider a two-stage process in which an oil and gas firm incurs positive initial setup cost K when entering the industry in stage one and upon entry, it competes for business in stage two. In the pure strategy subgame perfect Nash equilibria (SPNEs) no firm wishes to alter its entry decision given the decisions of the other firms. The equilibrium condition with J^* firms in the market can be defined as

$$\pi_{J^*} \geq K \quad and \quad \pi_{J^*+1} < K \tag{2.1}$$

where $\pi_{J^*}\,(\pi_{J^*+1})$ is the profit of each firm with $J^*\,(J^*+1)$ firms competing in the market. Now assume that firm simultaneously decides on the amount of oil to be produced ($q_j \geq 0$), the market supply function of oil can be written as $Q = \sum_{j=1}^{J} q_j = Jq_j$ Without the loss of generality, we further assume that each firm is able to produce oil at a constant marginal cost of $c \rightarrow 0$.

Consider the following inverse demand function of oil

$$P\left(Q\right) = a - bQ \tag{2.2}$$

where a and b are non-negative parameters, and $p\left(.\right)$ is the market price. Given other firms' output q_{Q_i}, firm i's maximization problem is:

$$\underset{q_i}{Max}\ \left(p\left(q_i + q_{Q_i}\right) * q_i\right) \tag{2.3}$$

where $Q \equiv q_i + q_{Q_i}$. Solving for the first-order condition of equation 2.3 and let $q_i^* = \frac{Q^*}{J}$, we obtain

$$p'\left(Q^*\right)\frac{Q^*}{J} + p\left(Q^*\right) = 0 \tag{2.4}$$

Combining equations 2.2 and 2.4, we obtain the equilibrium market output and clearing prices:

$$Q^* = \frac{aJ}{J+1} \quad and \quad p^* = \frac{a}{J+1} \tag{2.5}$$

The profit for each firm is:

$$\pi_{J^*} = \left(\frac{a}{J^*+1}\right)^2 \tag{2.6}$$

Solving for the equilibrium number of the entrants J^* gives

$$J^* = \frac{a}{\sqrt{K}} - 1 \tag{2.7}$$

Based on equations 2.5, 2.6 and 2.7, the equilibrium oil price falls and the quantity increases as the number of firms increases. In addition, as $J \to \infty$ the price approaches the competitive market equilibrium and each firm makes zero economic profits. Further, equation 2.7 suggests that as the initial setup cost K decreases, the number of firms active in the market increases.

For the petroleum industry, the initial setup or entry cost is primarily determined by the cost of drilling and exploration. Since 2012, the average drilling and completion cost has dramatically decreased due to the popularization of the combined use of horizontal drilling and hydraulic fracturing techniques. U.S. Energy Information Administration (2017) estimates that the reduction in drilling and exploration cost can be as high as XXXX%. Here, we assume the setup cost before the shale gas boom, $\overline{K}$, is higher than that after the shale boom, which is denoted as $\underline{K}$.

Prior to the shale boom, with a high entry cost $(\overline{K})$, as suggested by equation 2.7, there were only a limited number of super majors in the oil and gas industry, for example, the consortium of Seven Sisters in the US. and the New Seven Sisters including world suppliers from different countries. The Organization of the Petroleum Exporting Counties (OPEC), which are responsible for 40% of the worlds oil production (according to EIA), is a consortium of 13 countries and the single largest entity influencing the worlds oil supplies. The OPEC had monopoly power to determine the price of crude oil through production decisions. Therefore, before the shale gas boom when drilling cost was high, we might be able to model the oil price and quantity using the simple monopoly model assuming all major firms in the industry act together as a monopolist. The equilibrium quantity and price are

$$Q_m^* = \frac{a}{2} \quad \textit{and} \quad p_m^* = \frac{a}{2} \tag{2.8}$$

With the new technology developments and the subsequent lower setup cost ($\underline{K}$) after the shale gas boom, there are more firms enter the oil and gas industry. The new entered firms, competing in the market for price and profit; however, they do not have enough capacity to satisfy the entire demand of the market. In other words, their capacities are limited given conditions such as decreasing returns to scale or constrained capital. Kreps and Scheinkman (1983) show that the unique subgame perfect Nash equilibrium of price competition with capacity constraints will give the same outcome as the Cournot quantity competition.

Edgeworth (1925) suggests that with limited capacity there is a range within which the price will fluctuate. This range depends on the capacity of each firm. Consider the simplest duopoly case. Suppose one firm will charge a price at the marginal cost, c, and make zero profit, it can only sell up to its own capacity, k. The other firm could raise its price to the monopoly level to fulfill the rest of the demand.

For example, assume the duopoly setting with two firms which have the same limited capacity, k. Let the lowest and highest price of the range be $\underline{p}$ and $\overline{k}$. Suppose one firm chooses a price which is infinitely close to $\underline{p}$. The other firm may choose the monopoly price for the rest of the demand, $\overline{p} = \frac{a-k}{2}$. The two firms will be indifferent if and only if

$$k\underline{p} = (a - k - \overline{p})\,\overline{p} \tag{2.9}$$

which gives the lower bound of the price range and the profits of the two firms

$$\underline{p} = \frac{1}{k}\left(\frac{a-k}{2}\right)^2 \tag{2.10}$$

$$\underline{\pi} = \overline{\pi}\left(\frac{a-k}{2}\right)^2 \tag{2.11}$$

Levitan and Shubik (1972) derived a price game with the more realistic assumption of unequal capacities. They document that the firm with a lower limited capacity will act at the bottom range of price while the firm with higher capacity will act at the higher price range. This justifies the shale band concept in the U.S. oil market in recent years that oil prices fluctuate within a price band.

Prior the shale gas boom, the number of oil firms and productions in the U.S. is limited, with the price for WTI light sweet oil in the U.S. predominately determined by the global supply and demand conditions. With the new technology developments that dramatically lowered drilling and exploration costs from shale formations, the U.S. producers quickly gained bargaining power and started to affect crude oil prices. The newly emerging oil producers with new technologies and lower costs generally have more constrained capacities than the major traditional producers do. According to the discussion above and the theory in Levitan and Shubik (1972), they would operate with full capacity at a low profit margin. In a repeated dynamic game setting, the number of new firms will change accordingly in response to the change in setup cost, global demand, firm capacity, and market price. The aggregate oil market price fluctuates within the range in response to the change in the number of firms, global demand, and firm capacity. Therefore, all else equal, we would expect that changes in the number of oil rigs have a more significant impact on crude oil price after the shale gas boom. This impact should be much weaker before the shale gas boom because of the monopolistic nature due to the technology constraints and higher setup costs. And vice versa, changes in the crude oil price would also have a more significant impact on the number of oil rigs after the shale gas boom.

In the next section, we will discuss the empirical tests to verify this structural change in the energy industry.

3 Empirical Methods

To estimate the relationship between rig count and oil/natural gas prices, we rely on Vector autoregression (VAR) model that captures the linear interdependencies among multiple time series by incorporating own lagged values, the lagged values of the other variables, and an error term, as

$$X_t = \sum\nolimits_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t \tag{3.1}$$

where X_t represents the system of N endogenous variables, ε_t are the vectors of independently and identically distributed disturbances, Ω is the covariance matrix, and P is the lag length of the variables. In the present analysis, X_t is a column vector: $[price_t^{oil}, rig_t^{oil}, price_t^{gas}, rig_t^{gas}]'$.

Our first empirical analysis (talk about Granger causality test)

For a covariance stationary process there exist the moving averages representation as $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrix A_i obeys the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$ with A_0 being an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. The moving averages coefficients (or transformations such as impulse response functions or variance decomposition) provides the dynamics of the system, and can be used to construct commonly used innovation accounting measures, such as the impulse response functions and forecast error variance decomposition in equation. An impulse response is the reaction of any dynamic system in response to some external change. The impulse response describes the reaction of the system as a function of time (or possibly as a function of some other independent variable) that parameterizes the dynamic behavior of the system. The forecast error variance decomposition is a transformed version of impulse response functions.

We next construct information spillover indices for the four sequences, i.e., how much information can be extracted from one sequence when forecasting another variable, following the work by Diebold and Yilmaz (2009, 2011, 2012, 2014, 2015). The DY connectedness index builds upon the forecast error variance decomposition of the VAR model. The variance decomposition allows splitting the H-step ahead forecast error of each variable into parts that can be attributable to its own shocks and shocks from other variables, and hence indicates the amount of information each variable contributes to the variation of other variables in a forward-looking perspective. The forward-looking characteristic is appealing as it takes several months for the petroleum firms to start a new well exploration. Following the DY framework, elements of the decomposition matrix are subsequently aggregated to construct the directional connectedness from a variable to/from other variables, as well as the total connectedness within the system.

We compute variance decompositions following the generalized framework of Koop et al. (1996) and Pesaran and Shin (1998) that are invariant to the ordering of the variables. Specifically, the H-step ahead forecast error variance of variable i attributable to j is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i h_h \Omega e_j)^2}{\sum_{h=0}^{H-1} (e'_i h_h \Omega e_j)} \tag{3.2}$$

where σ_{jj} is the standard deviation of the error term of the j^{th} variable and e_i is a selection vector with one on the i^{th} element and zero otherwise.

To measure the relative importance of each random innovation to the variation of another variable, DY then normalize each entry of the variance decomposition matrix by the sum of the row entries to obtain the directional spillover index from variable j to i at forecast horizon H, denoted as $C_{i\leftarrow j}(H)$:

$$\tilde{\theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{3.3}$$

which implies the row entry for any i^{th} variable to be $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=1$, and the row sums across all variables equals N, i.e, $\sum_{j=1}^{N}\tilde{\theta}_{j}^{g}(H)=N$. Similarly, $C_{j\leftarrow i}(H)$ denotes the pair-wise directional spillover from i to j, and represents the relative contribution of variable i to j's variation. The net pairwise directional connectedness from j to i, defined as $C_{ij}(H)=C_{i\leftarrow j}(H)-C_{j\leftarrow i}(H)$, can be used to determine which variable is the information transmitter $C_{ij}(H)>0$and which variable is the information receiver $C_{ij}(H)<0$.

Additional connectedness indices can be constructed to evaluate the role of each variable in the overall information transmission within the system. Equations 3.4, 3.5, and 3.6 show the amount of information transmitted from all other variables to i, the information transmitted from i to all other variables, and the net information transmitted by i to the rest of the system, respectively:

$$C_{i\leftarrow\bullet}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{N} \tag{3.4}$$

$$C_{\bullet\leftarrow i}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}=\frac{\sum_{i=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N} \tag{3.5}$$

$$C_{i}(H)=C_{i\leftarrow\bullet}(H)-C_{\bullet\leftarrow i}(H) \tag{3.6}$$

Finally, the sum of the variance decompositions across all markets measures the system-wide connectedness, or how closely the system components are linked, as

$$C(H)=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N} \tag{3.7}$$

The connectedness horizon H is of interest because it helps to analyze the connectedness in short$-$ and long$-$runs. For instance, shocks to j may only affect the forecast error variance of with a lag, such that $C_{j\leftarrow i}(H)$ may be low at immediate horizons but increase as we move to more distant horizons.

Additionally, since one of our main hypotheses is that the information content in the rig count data may have evolved over time and that energy prices may have, we hence construct time-varying connectedness indices to capture evolution that may have occurred due to changes in the underlying economy and business cycles, improvement in drilling and exploration technologies, shifts in energy policies and regulations, and development in financial market environments. **For this purpose, we use the rolling-window approach, with 60 weeks being the window size, to construct the time-varying connectedness indices within the system.**

4 Results

We use crude oil prices as the West Texas Intermediate (WTI) - Cushing, Oklahoma, dollars per barrel, not seasonally adjusted series and adjust for real term using the Consumer Price Index for All Urban Consumers: All Items (Index 1982-84=100 Seasonally). We use the U.S. crude oil rotary rig in operation as the proxy for the activities of all the regional oil producers. The shale gas is another important feature in the U.S. energy markets. To control for the possible effects of the shale gas, we use the Henry Hub Natural Gas Spot Price (dollars per million BTU), not seasonally adjusted and adjust for real term using the Consumer Price Index for All Urban Consumers: All Items (Index 1982-84=100 Seasonally). The U.S natural gas rotary rig in operation is used as a proxy for the regional shale gas producers activities. The crude oil price, natural gas price, and CPI index are downloaded from Federal Reserve Economic Data (FRED). We use CPI adjusted crude oil price, and natural gas prices and take the growth rates to label these variables as ROP and RGP respectively. We use the U.S. Energy Information Administration database to retrieve the U.S. Crude Oil Rotary Rigs in Operation and the U.S. Natural Gas Rotary Rigs in Operation. We label these variables as OR and GR respectively in this study. The data is monthly from 1997 January to 2019 February.

4.1 Trend Diagram

Figure 1 panel (a) in left y-axis exhibits the trends of crude oil prices of the West Texas Intermediate (WTI) − Cushing, Oklahoma in Dollars per Barrel along with numbers of crude oil rotary rig in operations in right y-axis. Post-2014, the nominal oil prices ranges in between \$32.74 to \$106.07 mostly fluctuating around the range of \$20 to \$55 per barrel in the nominal level term. This is consistent with the Shale-Band term coined by Olivier Jakob, managing director of Petromatrix, a consultancy based in Switzerland. Figure 1 panel (b) in left y-axis exhibits the trend of the Henry Hub Natural Gas Spot Price in Dollars per Million BTU along with the with numbers of crude gas rotary rig in operations in right y-axis.

[Insert Figure 1 here]

The number of U.S. crude oil rotary rigs in operation increased dramatically since 2010, decreased since 2015, and bounced back since the beginning of 2016. The number of U.S. natural gas rotary rigs in operation decreased since 2009 and increased since 2016. The numbers of oil rigs and gas rigs have similar patterns since 2015. For the past two decades prior 2008 financial crisis, the numbers of oil rigs and gas rigs are relatively stable over time.

4.2 Descriptive Statistics

Table 1 Panel A and Panel B show summary statistics for the level and the growth rate of CPI adjusted natural gas prices, gas rig in operation, CPI adjusted crude oil prices, and oil rigs in operation respectively. The Augmented Dickey Fuller (ADF) tests show that level variables are non-stationary, and growth rates are stationary.

[Insert Table 1 here]

Table 2 shows the pairwise correlation among CPI adjusted natural gas prices, gas rig in operation, CPI adjusted crude oil prices, and oil rigs in operation respectively. The oil and gas prices are positively correlated. The oil rigs and gas rigs are also positively correlated.

[Insert Table 2 here]

4.3 Granger-Causality (Full Sample)

[Insert Table 3 here]

Table 3 shows two types of Granger-Causality test: pair-wise Granger-Causality tests (Panel A), and instantaneous Granger-Causality tests (Panel B).

Pair-wise Granger-Causality test perform the null hypothesis that variable presented in row does not Granger-cause variable presented in column, then reports the $F-$statistics. For example, the $F-$statistics of 12.73 tests the null of real gas price does not Granger-cause itself. The $F-$statistics is significant suggesting failure to reject such null hypothesis thus provides evidence previous period real gas prices possible explains current period real gas prices. Another example can be the $F-$statistics of 5.62, which test the null hypothesis of gas rigs do not Granger-cause oil rigs. The $F-$ statistics is significantly non-zero indicating previous periods gas rigs possibly predicts the current period oil rigs.

Furthermore, we also find the evidences of gas rigs Granger-causing gas rigs ($F-$statistics = 80.82***); real oil price Granger-causing oil rigs ($F-$statistics = 8.69***); oil rigs Granger-causing gas rigs ($F-$statistics = 4.0***); and oil rigs granger causing itself ($F-$statistics = 56.07***).

Instantaneous Granger-Causality test perform the null hypothesis that histories of all observable variables do not Granger-cause variable presented in row, then reports the Wald statistics. We find histories of all observable variables Granger-cause real gas price but not the gas rigs. Similarly, histories of all observable variables Granger-cause real oil prices but not the oil rigs.

4.4 Impulse Response Function or Cumulative IRF (Full Sample) (Xiaoli please choose)

Please interpret this Cumulative IRF.

[Insert Figure 2 here]

4.5 Total Connectedness Table (Full Sample)

See the interpretations in the table footnotes.

[Insert Table 4 here]

4.6 Total Connectedness Rolling Window

[Insert Figure 3 here]

4.7 Net Connectedness Rolling Window Real Gas Price

[Insert Figure 4 here]

4.8 Net Connectedness Rolling Window Gas Rigs

[Insert Figure 7 here]

4.9 Net Connectedness Rolling Window Real Oil Price

[Insert Figure 6 here]

4.10 Net Connectedness Rolling Window Oil Rigs

[Insert Figure 7 here]

5 Discussion and Conclusions

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Tables

Table 1: Descriptive Statistics (From January 1997 to April 2019 Monthly)

Variables	Mean	Median	Max	Min	Std dev	Skew	Kurt	JB-test	ADF-test
					Panel A: Level (CPI adjusted)				
Real gas price	2.125	1.754	6.886	0.706	1.137	-8.7E+07	5.09E+10	187.199***	-3.123
Gas rigs	717.716	690.5	1585	82	414.394	5.653	16.378	13.17***	-1.64
Real oil price	26.307	23.516	64.36	6.929	12.01	-66306.3	3532033	15.075***	-1.972
Oil rigs	531.146	345.5	1596	108	431.352	3.399	10.675	54.632***	-2.17
					Panel B: Growth rate				
Real gas price	0.013	0.005	1.106	-0.586	0.181	1.438	9.493	494.893***	-6.328***
Gas rigs	-0.002	0.005	0.154	-0.236	0.052	-1.164	6.504	119.623***	-5.877***
Real oil price	0.006	0.009	0.353	-0.318	0.094	0.055	3.795	9.283***	-7.136***
Oil rigs	0.006	0.009	0.263	-0.229	0.071	-0.215	4.309	22.168***	-4.561***

Notes: The ***, **, and * represent 1%, 5%, and 10% level of significance, respectively. Sample ranges from January 1997 to April 2019. Real gas price, Gas rigs, Real oil price, Oil rigs represents monthly growth rate of Henry Hub Natural Gas Spot Price (CPI adjusted Dollars per Million BTU), U.S. Crude Gas Rotary Rigs in Operation, WTI Crude Oil Prices (CPI adjusted Dollars per Barrel) and U.S. Crude Oil Rotary Rigs in Operation respectively. The CPI Index (1982-1984=100, Seasonally Adjusted) represents Consumer Price Index for All Urban Consumers: All Items, avialable from the Federal Reserve Bank of St. Louis website.

Table 2: Correlation Matrix (From January 1997 to April 2019 Monthly)

	Real gas price	Gas rigs	Real oil price
Gas rigs	0.03		
Real oil price	0.14*	0.03	
Oil rigs	0.08	0.29****	-0.06

Notes: The ***, **, and * represent 1%, 5%, and 10% level of significance, respectively.

Table 3: Granger Causality

Variables	Panel: A Pairwise Granger Causality				Panel :B Granger Causality
	Real gas price	Gas rigs	Real oil price	Oil rigs	All other variables
Real gas price	12.73***	0.1	0.94	1.03	2.46***
Gas rigs	2.02	80.82***	0.7	5.62**	1.29
Real oil price	2.25	2.09	1.95	8.69***	6.56***
Oil rigs	0.01	4.0*	1.17	56.07***	1.29

Notes: The ***, **, and * represent 1%, 5%, and 10% level of significance, respectively. Pair-wise Granger-Causality test perform the null hypothesis that variable presented in row does not Granger-cause variable presented in column, then reports the $F-$statistics. Instantaneous Granger-Causality test perform the null hypothesis that histories of all observable variables do not Granger-cause variable presented in row, then reports the Wald statistics.

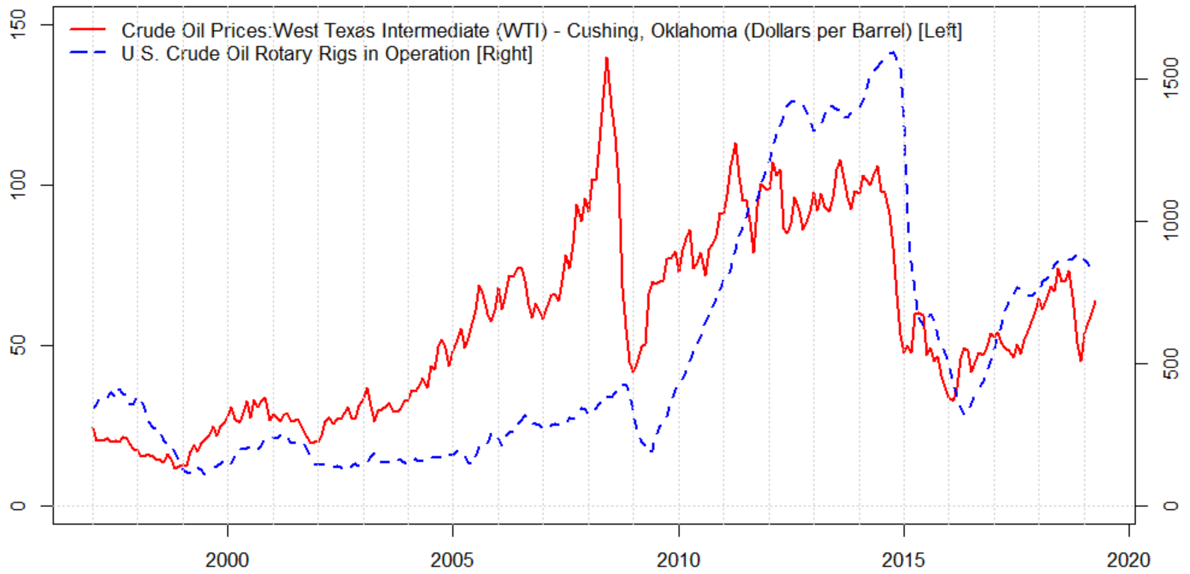
Table 4: Connectedness Full Sample, $H = 6$

Variables	Real gas price	Gas rigs	Real oil price	Oil rigs	$C_{\bullet\leftarrow i}(H)$
Real gas price	96.10	1.14	2.06	0.70	*3.90*
Gas rigs	7.04	74.92	12.27	5.78	*25.08*
Real oil price	3.29	2.92	93.04	0.76	*6.96*
Oil rigs	2.31	5.38	22.30	70.01	*29.99*
$C_{i\leftarrow\bullet}(H)$	*12.63*	*9.44*	*36.63*	*7.23*	-
$C_i(H) = C_{i\leftarrow\bullet}(H) - C_{\bullet\leftarrow i}(H)$	***8.73***	***-15.64***	***29.67***	***-22.76***	$C(H)=$<u>***16.48***</u>

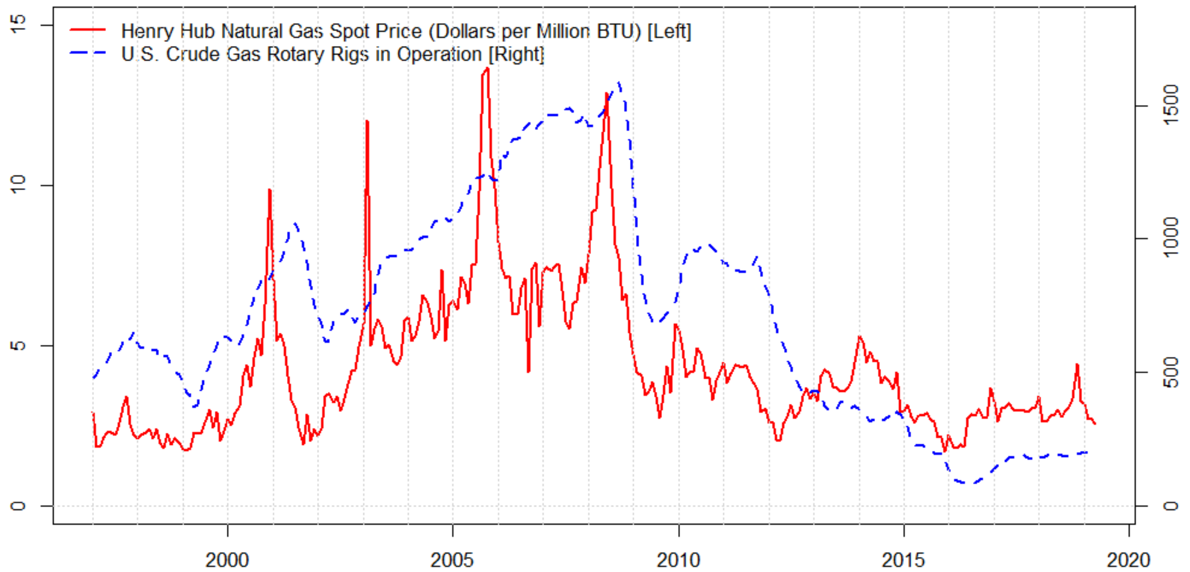
Notes: $C_{\bullet\leftarrow i}(H)$, shown in italic, represents total row sums except respective diagonal element which indicates total information received. $C_{i\leftarrow\bullet}(H)$, shown in italic, represents total column sums except respective diagonal element which indicates total information spillover. $C_i(H)$, given in italic bold, show the net information transmitted. $C(H)$, given in italic, bold, and underlined, shows total connectedness.

Figures

Figure 1: Tread Diagram (From January 1997 to April 2019)

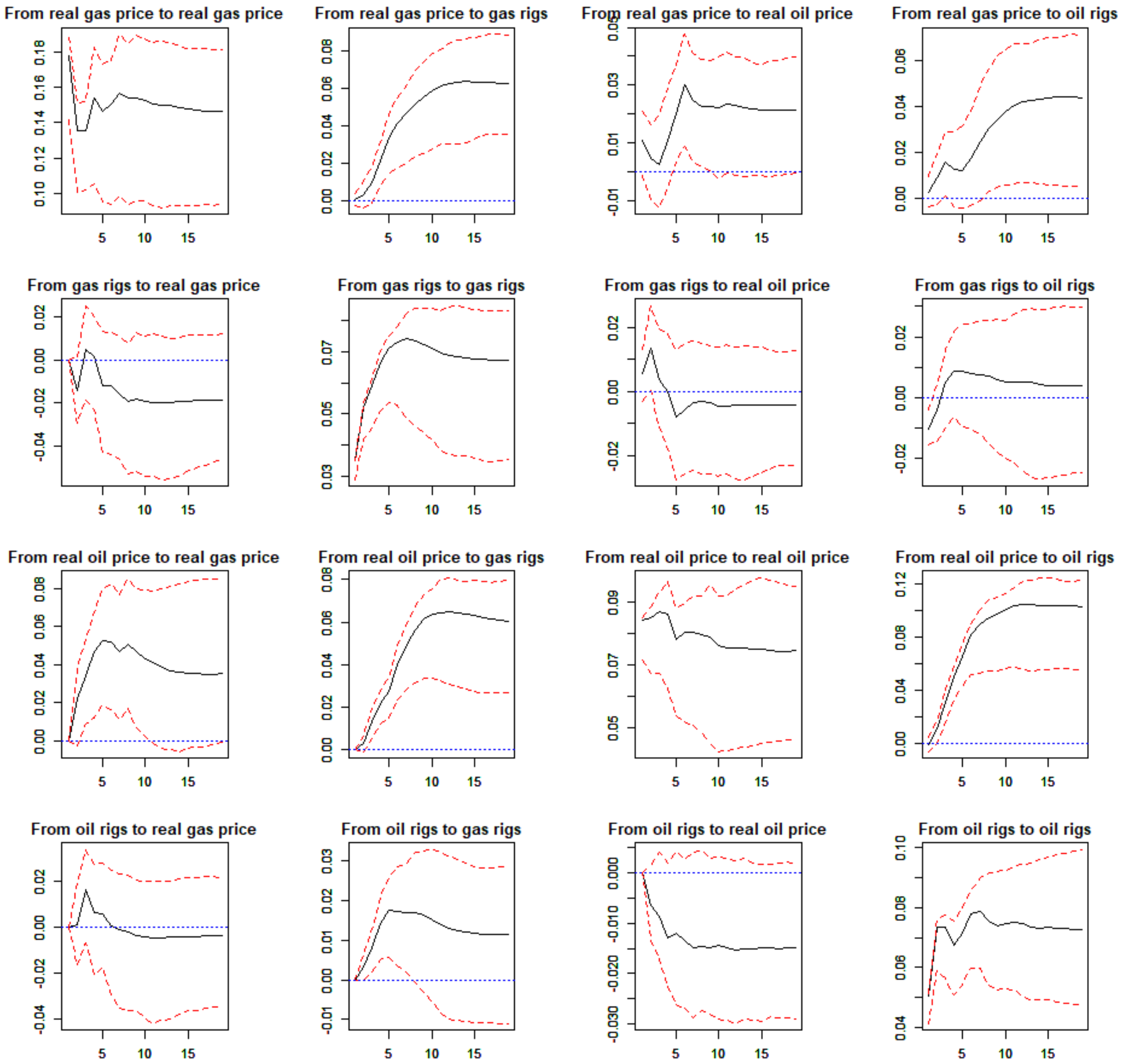


(a)



(b)

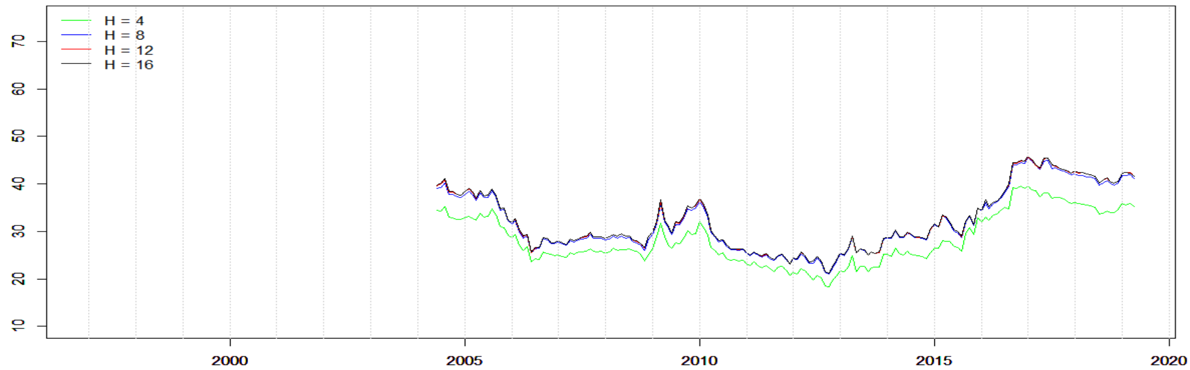
Figure 2: Impulse Response Function (One standard deviation shock, with 90% confidence interval)



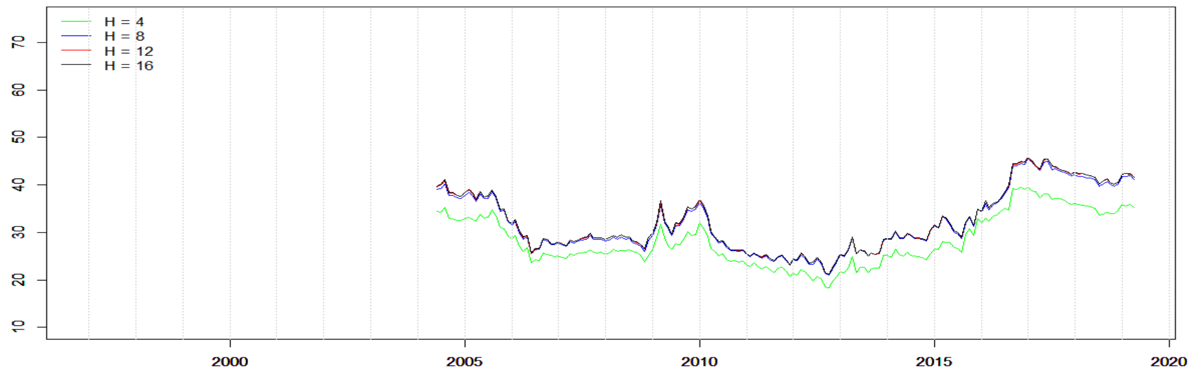
(a)

Figure 3: Total Connectedness (Different Rolling Windows and Different Horizons)

(a) Window = 60 months

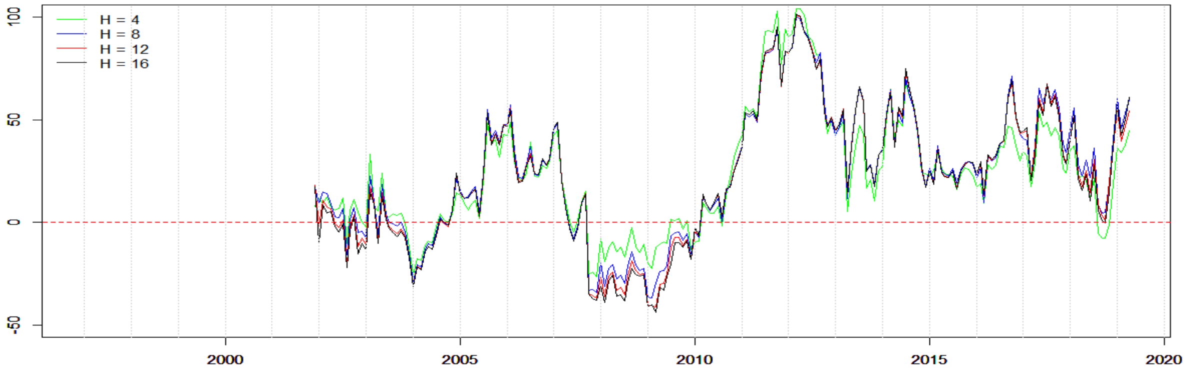


(b) Window = 90 months

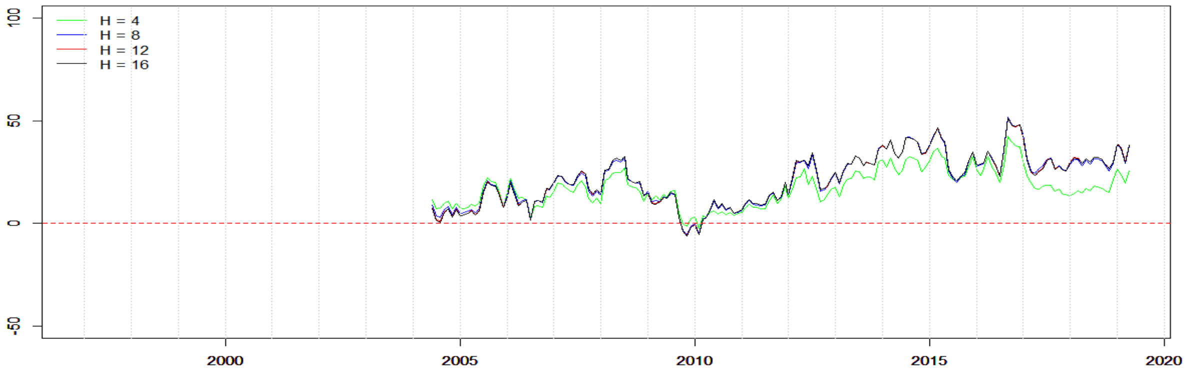


(c) Window = 120 months

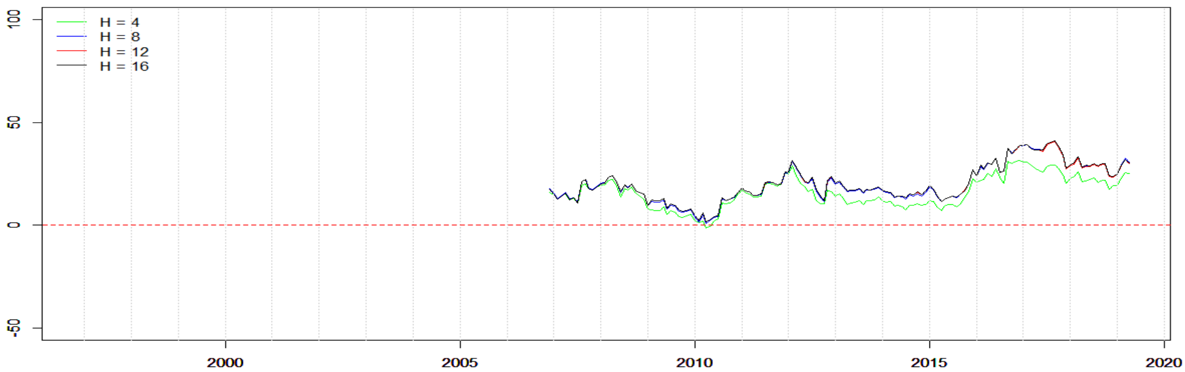
Figure 4: Net Connectedness Real Gas Prices (Different Rolling Windows and Different Horizons)



(a) Window = 60 months

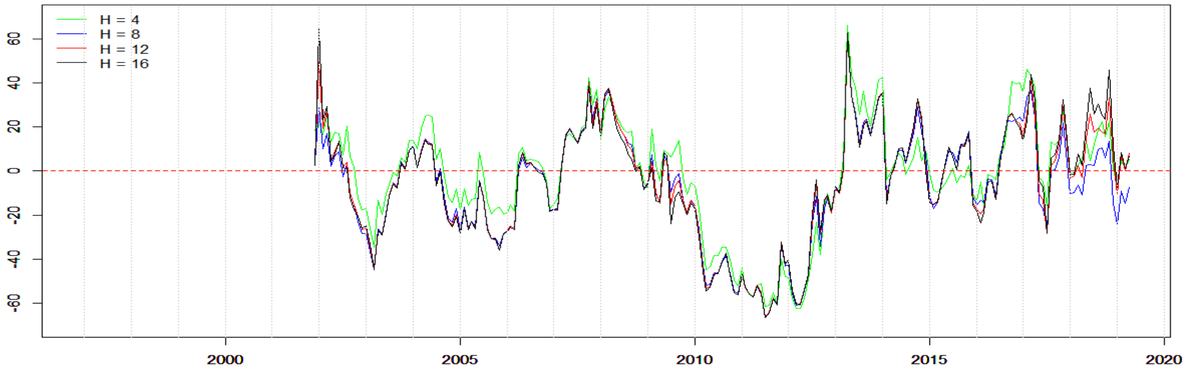


(b) Window = 90 months

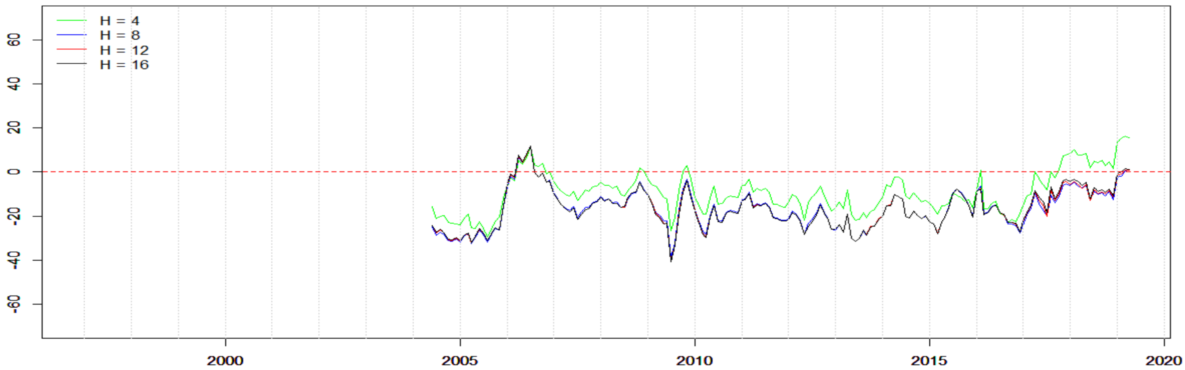


(c) Window = 120 months

Figure 5: Net Connectedness Real Gas Rigs (Different Rolling Windows and Different Horizons)



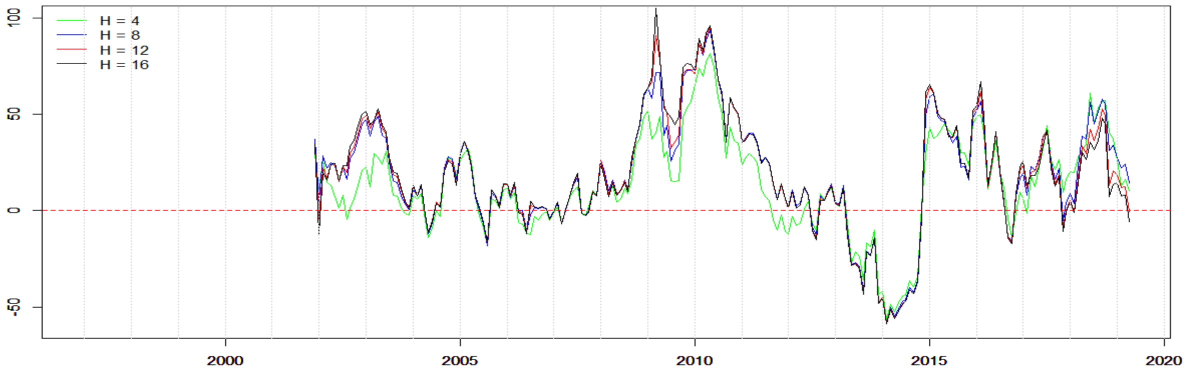
(a) Window = 60 months



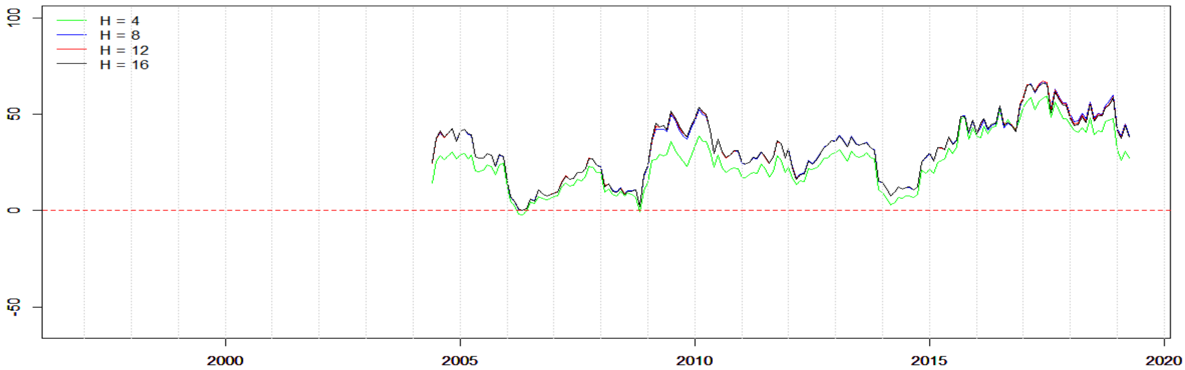
(b) Window = 90 months

(c) Window = 120 months

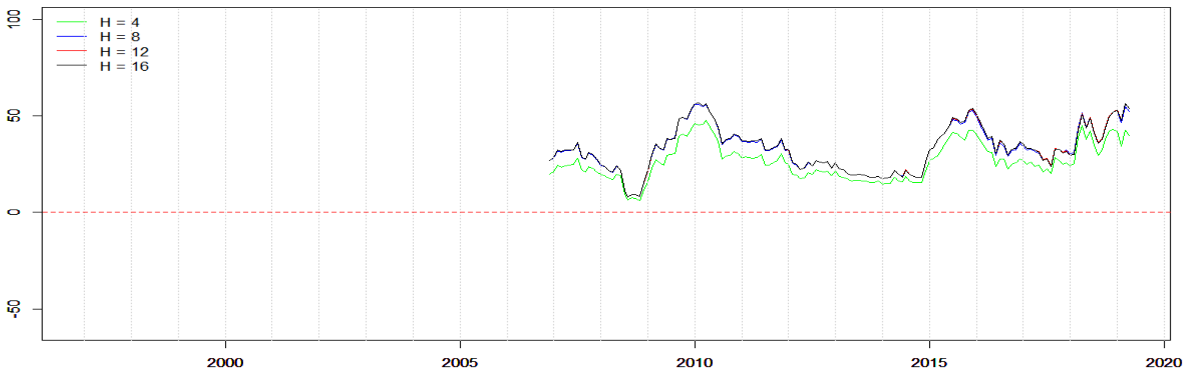
Figure 6: Net Connectedness Real Oil Prices (Different Rolling Windows and Different Horizons)



(a) Window = 60 months

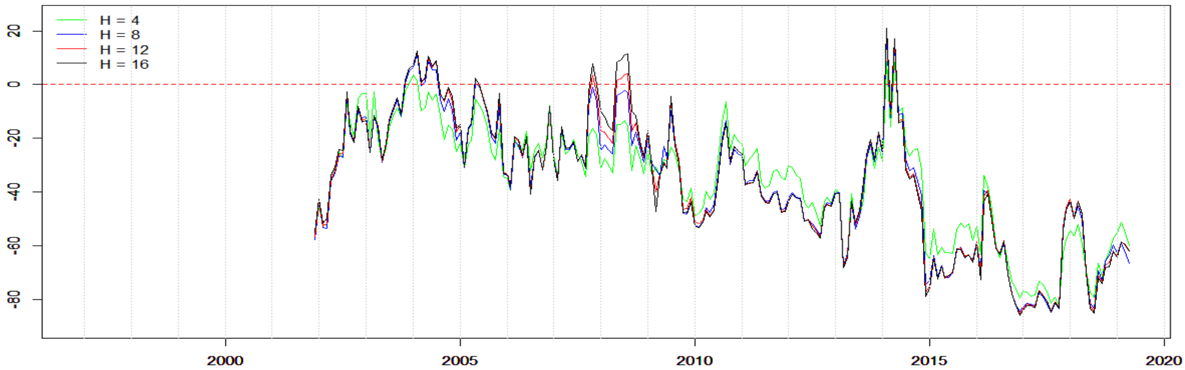


(b) Window = 90 months

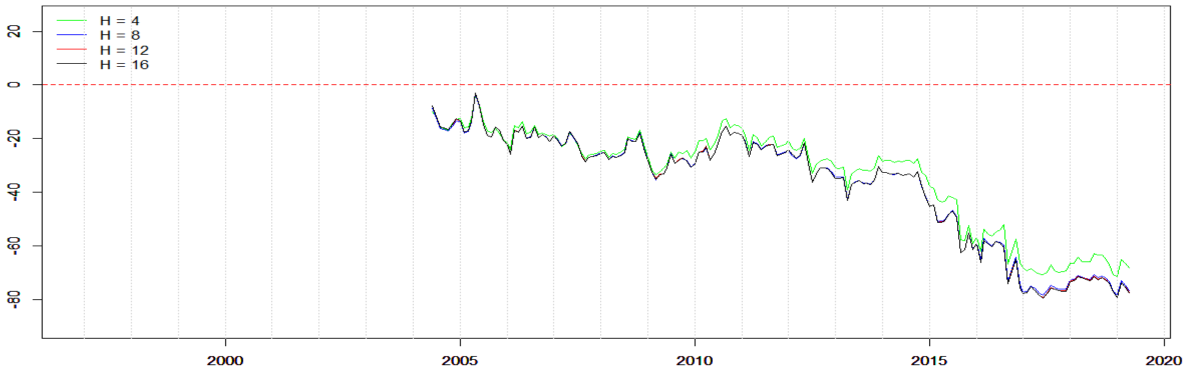


(c) Window = 120 months

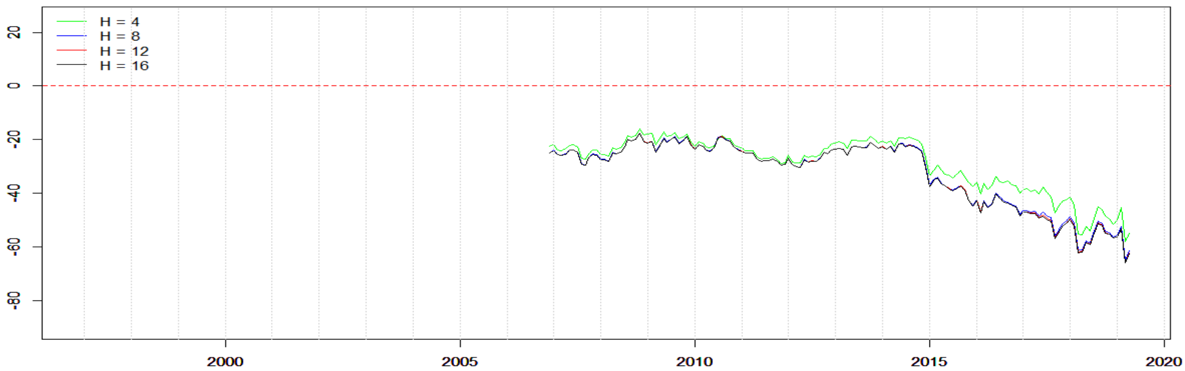
Figure 7: Net Connectedness Real Oil Rigs (Different Rolling Windows and Different Horizons)



(a) Window = 60 months



(b) Window = 90 months



(c) Window = 120 months