How the U.S. Oil and Gas Producers Respond on Prices: A Pre and Post Shale Boom Analysis

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May 14, 2019

ABSTRACT

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1. Introduction

After the oil market collapse of June 2014, the oil and gas industry has been all abuzz about the "Shale-Band" concept. The term was coined back in May of 2015 by Olivier Jakob, managing director of Petromatrix, a consultancy based in Switzerland. He said that the U.S. oil production trends would be determined by two price points—$45 a barrel, below which oil produced from shale formations would drop off, and $65 a barrel, above which there would be "massive [shale] production coming online." (Salvaterra, 2016). Jakob later revised the range to 40$ to 60$ a barrel price hinting that shale producers are keeping the taps on at lower prices.

The "Shale-Band" theory also seems to be supported by the data (see Figure-1). Shale oil comprises roughly half of U. S. oil output. The number of U. S. oil rigs fell by 158 from early December 2016 to mid-March of 2017 when WTI, the U. S. oil price benchmark, was trading below $40 a barrel, according to oil services firms Baker Hughes. Further U.S. crude-oil production fell by 78,000 barrels per day, according to the U. S. Energy Information Administration (EIA, 2017). As the meantime, when WTI crude oil prices are above $55, the U. S. oil rig counts increase dramatically. The rapid change in several U. S. oil rigs also influenced by the average drilling & completion costs. With modern technology development, the construction time and cost for shale rigs have been decreased substantially. There seem to exist a causal relationship; however, a detailed analysis is necessary.

Nevertheless, the shale band theory is nothing new but a variation of the equilibrium model of the demand and supply. In a perfectly competitive market, the equilibrium price, in the long run, should equal the minimum value of the average total cost. As the average overall cost decreases, the equilibrium price should decrease accordingly. However, given the historical nature of oil drilling industry and the monopoly power of OPEC, in the past decades, the oil market was not competitive enough (constrained by substantial drilling costs and high entry threshold). Therefore oil prices are not only driven by the demand and supply but also depending on the policies and decisions such as OPEC's agreements about international oil production. In recent years, with the development of new technology, especially the hydraulic fraction, the average oil drilling and completion cost decreases dramatically, and smaller investors can enter the oil drilling industry. More competition drives the oil price approaching the equilibrium and moving within a band. As the drilling cost decreases, the medium of the band is expected to decrease accordingly.

In this paper first, we provide a simple game theoretical setting on how the producers behave upon the price changes and how the producer's responses to price changes can affect the prices itself. Then, we empirically investigate the evolutionary relationships among changes in oil prices, gas prices and their respective rig counts and expectation toward the various level of future uncertainties. Our results are provided with several robustness tests in which we take into consideration of other pertinent variables, optimal time lags, multiple sliding temporal windows, causality and expectation toward several future horizons. Such evolutionary relationship between changes in oil and gas prices and changes in their respective rig counts allows us: to investigate how producers cope themselves in various price regimes; the evolution of the causal relationship and; evolution and spillover of risk or information transmissions. Our results and analysis are of significant interest for researchers, analyst, investors, and policymakers, whether they are oil/gas companies, commercial banks or investment banks.

This research is intriguing mainly for the following reasons. First, the US regional tight oil producer is gaining the market power hence understanding the dynamics of regional producers helps to evaluate the US producers' stance. Secondly, the firm position of US regional producer who operates in free-market setting threatens OPEC producers as the "U.S. producers are enjoying a second wave of growth so extraordinary that in 2018 their increase in liquids production could equal global demand growth" (Meredith, 2018). The US exuberating on shale oil production is forecasted be on well-placed to overtake the likes of Saudi Arabia and Russia as the world's leading energy producer by 2019 (Meredith, 2018). Thirdly, we find no recent development in the literature that econometrically estimate and validate "Shale Band" theory. Hence, in this paper, we provide an intuitive theoretical argument on the behavior of US shale oil producer and provide an econometric estimation of how the causal effects of prices and production are influencing each other.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 explains the institutional details on what is rig and how it works. Section 4 models a generic Cournot competition model to set up the hypothesis of our study. Section 5 provides the econometric framework of Vector autoregression (VAR) model; Diebold and Yilmaz"s Variance decomposition method to estimate total connectedness and net connectedness measures; and sample connectedness based on the rolling window approach. Section 6 discusses the data, descriptive statistics and empirical results using various graphs along with robustness checks. Finally, we conclude.

2. Literature Reviews

Voluminous researches have investigated the behavior of crude oil and natural gas prices while only a few studies focus on oil or gas regarding the rig counts. The recent papers that discuss how higher rates stimulate investment in the U.S. onshore drilling industry are Kellogg (2011) and Kellogg (2014). With the case of the U.S. onshore drilling industry which comprises of producers and drilling contractors, Kellogg (2011) provides a theoretical explanation of the economic consequences of learning-by-doing or that the hypothesis that unit costs decrease with cumulative production in the oil and gas industry. He finds that compare to drilling rig who frequently changes contracting partners, the drilling rig who contracts with the same partners are twice likely to improve its productivity. Therefore, producers are more likely to work with a drilling rig that has substantial prior experience. While Kellogg (2014) uses a dynamic model of firms to provide the theory of the responses of investment to changes in uncertainty and uses data on oil drilling in Texas and the expected volatility of the future oil price to provide a micro-empirical estimation. Such theory is critical because the oil and gas industry has relatively high sunken cost or the irreversible investment – the 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 reaction 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.

The oil and gas industry producers issue a request for quotation (RFQ) from drillers, and once drillers are awarded the contracts, the drillers crew install the rig and start the process of extraction of reserves. Therefore, the changes in prices of oil or gas only affect the producers and not the driller. Thus, a lagged relationship between the effect of prices and rig count can be observed in the data. Black & Lafrance (1998) develop a model of oil supply from known reserves and incorporate geological and engineering principles known as maximum efficient recovery (MER) to explain that the relationship between changes in oil prices and rig counts may not be that obvious and direct because of the presence of the lagged response which is due to the geoengineering principles. Similarly, Khalifa, Caporin, & Hammoudeh (2017) empirically verified that up to one quarter lagged relation for the impact of changes in oil prices on rig counts. They use quantile regression and quantile-on-quantile models to test a non-linear relationship between oil price and rig counts, but such evidence of non-linearity is weak in most recent years where the relationship between the variables has stabilized. Such a non-linear relationship may exist because of the effects of the changes in oil well productivity, rig efficiency, drilling costs, commodity inflation, hedging, changes in inventories (Hunt & Ninomiya, 2003).

Khalifa et al. (2017) reviews three dimension on how the oil price affect the rig counts and consequently to the oil supply– the drilling speed or productivity (Osmundsen, Roll, & Tveteras, 2012; Osmundsen, Roll, & Tveterås, 2010; Osmundsen, Sørenes, & Toft, 2008), well productivity (Fattouh, Poudineh, & Sen, 2016) and changes in numbers of rigs due to change in prices (Ringlund, Rosendahl, & Skjerpen, 2008). Our paper briefly contributes to the first two dimensions but our research in primarily elaborate in the third dimension to explain changes in numbers of rigs due to change in prices.

Osmundsen et al. (2008) relates the Norwegian experiences of rig shortage due to the high cost and examines whether changes in the contract format incentive the drilling contractors to innovate new technologies and solution to increase the drilling efficiency and reservoir utilization. Osmundsen et al. (2010) analyses the development in drilling productivity in exploration wells at the Norwegian continental shelf with a generic translog econometric model using panel sample from 1966 to 2008 available from the Norwegian Petroleum Directorate (NPD). Their paper explains that the falling oil prices combined with the sticky costs cause project postponement and a dramatic fall in drilling productivity. Similarly, Osmundsen et al. (2012) analyses the effects of different types of experience (or learning) on exploration drilling productivity and examine how the change in overall activity levels affects the drilling speed over time. They find that the experience of the drilling facility has no significant effect on productivity for the sample average well. Therefore they put forward a rationale that averages the learning effect is offset by the vintage impact of the drilling facility then identify situations where learning effects are particularly important, to the extent that learning outcome dominates adverse effects of drilling activity. Both papers explain the Norwegian experience when the cost of drilling is rising or sticky on high ranges prior 2008, however, in our paper we examine that recent shale gas development has reduced the cost of drilling and extraction drastically and show how regional producers in the US cope with drilling activities/productivity with respect to price changes using robust models. Therefore, we contribute to explain the US experiences when the costs of producing are falling.

Fattouh et al. (2016) explain Saudi Arabia's oil policy to maintaining its share in key markets and maximizing long-term revenue under uncertainty imposes by the US shale development using a simple game theoretic setting. He explains that the Saudi Arabia's oil policy could change as the trade-off between revenue maximization and market share evolves, and as new information to the market arrives especially the arrival of a new source of supply, will keep the market second-guessing and will continue to shape market expectations and to influence market outcomes. Our study relates with Fattouh et al. (2016) as we also explain the dynamics using a game theoretical approach, however, the point of divergence of our research is that we laid out our theoretical setting in terms of US regional producer's perspective. We relate that the shale gas development shifts a monopoly power toward a more competitive power setting among US local producers. Therefore, they respond quickly to the higher price by producing more thus generates higher supply and again push the price back. We relate such as "Shale band" concept first brought up in May 2015 by Olivier Jakob, the director of Petromatrix, a consultancy company that publishes daily notes on the oil markets.

Baffes, Kose, Ohnsorge, & Stocker (2015) explain the oil price (which was relative stability at around $105 per barrel (bbl) during 2010-2014) plunge of the June 2014 as significant but not unprecedented event and provides causes and consequence of that event. This latest episode parallels with the price collapse in 1985-86, which followed a period of substantial expansion of supply from non-OPEC countries and the final decision by OPEC to forgo price targeting and increase production (Baffes et al., 2015). Their paper explains supply (much more than demand) factors have accounted for the lion's share of the latest plunge in oil prices which comprise of several years of upward surprises in the production of unconventional oil; weakening global demand; a significant shift in OPEC policy[1]; unwinding of some geopolitical risks; and an

[1] As explained by (Baffes et al., 2015), "OPEC's decision to abandon price targeting in November 2014 also has important similarities to its actions during the 1985-86 episode. Following the 1979 peak in oil prices, OPEC reduced its supply to maintain high prices. Upholding its price target necessitated the cartel slashing its oil supply over the following six years, from 30 mb/d in 1979 to 16 mb/d in 1985. However, despite such a drastic supply cut,

appreciation of the U.S. dollar as multiple sources of cause for oil price fall. Rather than explain the global causes and consequence as Baffes et al. (2015), our paper examines the effects of prices changes in the rig counts in econometric estimation.

Ringlund et al. (2008) analyze how oilrig activity in different non-OPEC regions is affected by the crude oil price using dynamic structural time series regression models augmented with the latent components capturing trend and seasonality. They show a positive relationship and the long-run price elasticity for oilrig activity in non-OPEC countries is around unity. In relation, Black & Lafrance (1998)and Khalifa et al. (2017) examines the importance of the lags in the prices and rig counts.

In terms of modeling, Mohn (2008) explains oil producers behavior with standard neoclassical framework and estimates econometrically with a vector error correction (VEC) model and finds that reserve additions are enhanced by an increase in the oil price, due to responses both in effort and efficiency of exploration, therefore, oil producers accept higher exploration risk in response to an oil price increase. The author uses three-year moving averages for their endogenous variables changes in drilling efforts, discovery rates, and average discovery size. Similarly, Mohn & Osmundsen (2011) explain the asymmetric dynamics and uncertainty in oil and gas investment with the use of the error correction model on annual data from 1965 to 2004 and find week short-term effects but pronounced long-term impacts of oil prices on exploration activity in Norway. Toews & Naumov (2015) uses quarterly real oil price, global drilling activity and costs of drilling from 1992 to 2012 and estimate a three-dimensional structural vector autoregression model. They find a unidirectional Granger causality from changes in real oil prices to rig counts with a 4 to 6 quarter lags. For the VAR model with k variables and p lags of each of the variables in each equation requires to estimate $\left(k+pk^2\right)$ parameters to be estimated. Toews & Naumov (2015) may lack the power to explain with VAR model because their VAR model comprises of with 3 variables say with 4 lags requires to estimate $\left(3+4*3^2\right)=39$ various parameters using about 80 observations (quarterly data on 20 years). In our study we use monthly data with maximum four

real oil prices declined 20 percent during this period. In response, OPEC began increasing supplies (to 18 mb/d by December 1985 from 13.7 mb/d in June 1985). Partly because of this policy change, oil prices collapsed and remained low for almost two decades (World Bank, 2009). In response to the new lows in prices reached after the East Asian financial crisis, OPEC started setting a target price range of $25-35/bbl. The range was changed to $100-110/bbl before the 2008 financial crisis.”.

lags and our observation for estimation monthly from September 1987 till the December of 2017. Furthermore, we also use at-least about 60 to maximum 120 months rolling window for the VAR estimation. While most study includes impulse response function, we venture to explain the variance decompositions. Variance decomposition will decompose sources of the variance for each variable of interest.

3. What is rig and how it works?

The geologic formations beneath the Earth's surface in which the oil and gas reserves are found are known as the "fields." At least three different parties (leaseholder, producer, and drillers) exist for oil and gas production from the fields. First is leaseholder who has mineral rights. Second is the exploration and production companies (producers henceforth) who are equipped with in-depth geological information and provide engineering decision related to well design, well and drilling procedures. Before operating on this field to extract, process and sale the reserves, a producer must at first obtain the leases from the holders of that field's mineral rights. Such lease grants a right to operate in a small part of an area, therefore, several distinct producers hold different leases granted by a lease holding producer. The producers initiate the contracting process by the issuance of a request for quotation (RFQ) from drillers.

An RFQ comprises of the technical specifications of the well to be drilled, its depths, types of steel casing to be installed in the well and properties of the "drilling mud" to be pumped through the borehole during drilling. The third is the drillers who own the drilling rigs and employs the drilling crews. The geological variation across fields vary considerably in term of types of rocks and how deep the reserves are located. About 3000 feet deep can be drilled in a few days, and the labor and drilling rig rental can cost to few thousand dollars while other around 20000 feet deep can require several months of periods and the labor and drilling rig rental can cost to millions of dollars. These costs sunken costs are irreversible investments. The drilling in unexplored filed is known as "wildcats" well; drilling on previously explored fields are known as "developments" well whereas drilling late in a field's life is known as "infill" well. The Wildcats well intend to find the new productive areas while developments well and infill well aim to enhance the field productions. A rig is a machine that rotates the drill pipe from the surface to drill a new well (or sidetracking an existing one) to explore for, develop and produce oil. The rig is a tall derrick that allows the pipe to be drawn in and out of the well and a motor spins the drill pipe and drill bit during drilling. The size of drill determines a rig's "depth rating"– the depth to which the rig is recommended to drill. Rigs are mobile, and upon requirement, the driller can be easily be moved to a different location within a field, however, runs more than 50 miles may take several days and results in charging fees to the producers requesting the move. While under a contract, rigs operate 24 hours a day and 7 days a week with three 8-hours shifts crews.

News widely reports the numbers of drilling rigs ("rig counts") in operations and investors follow the rig counts closely because the rig counts serve as an indicator of performance and health of the oil and gas industry (Apergis, Ewing, & Payne, 2017). Generally, higher/lower prices of hydrocarbon commodities incentives producers to produce more/less; thus, higher/lower drilling operations is associated with the higher/lower price of hydrocarbon commodities. On average, drilling operations are seeming to follow three months of lags (Kellogg, 2011).

4. Theoretical framework

Consider oil as a homogeneous product. Each firm's oil production is a unique cost function, $C(q_j)$, and the marginal cost is $C'(q_j)$. The total quantity supplied is the sum of oil produced by each firm, $Q=\sum_{j=1}^{J} q_j$, where J is the total number of firms. We assume the number of oil rigs as a proxy for the number of firms and each rig produces different quantity q_j.

Assume a standard price function as $P(Q)=a-Q=a-\sum_{j=1}^{J} q_j$, where the price is a function of total production and a is the choke price. Now, consider a simple Cournot competition setting where each j^{th} firm tries to maximize its profit by producing $q_j \geq 0$. Their maximizing profit function is given by:

$$\max \pi_j = P(Q)q_j - C'(q_j)q_j = \left(a - Q - C'(q_j)\right)q_j \tag{1}$$

The first order condition of the above maximization problem is given as $q_j^* = \dfrac{a-\sum_{i\neq j}^{J} q_i - C'(q_j)}{2}$ and then the equilibrium profit of any j^{th} firm can be expressed as

$$\pi_j^* = \left(a - \sum_{j=1}^{J} q_j^* - C'(q_j^*)\right)q_j^* = \left(P(Q^*) - C'(q_j^*)\right)q_j^* \tag{2}$$

This shows that the profit of the firms depends upon the equilibrium price level, marginal cost to produce equilibrium quantity q_j^*, and also the number of firms J. Now we can create a system of equations in which oil price, cost, total quantity demand and supply, and the number of rigs can be solved together.

Before the shale gas boom, the crude oil market is not competitive enough, and the market power is in the hands of OPEC. The number of firms and productions in the U.S. are limited. Therefore, the optimal profit discussed in Equation (2) cannot be achieved because their ability to adjust output according to the price change is constrained. With the new technology developments, the drilling and completion costs decrease dramatically, and the regional oil producers quickly gain bargaining power. With the shale gas boom, the U.S local oil producers have become the world's marginal producers, who produce the extra barrels of oil when oil prices are higher than the marginal costs. Now the U.S. regional oil producers, not OPEC, are the one to decide the market price of crude oil. As in all competitive markets, the price and quantity will interact with each other which boils down to equilibrium and, this leads to the situation described in the shale band theory. Therefore, based on the simple optimal profitability function derived above, we propose the following hypotheses:

H1. Changes in price will have an impact on the number of oil rigs in the U.S.; however, this impact is weaker before the shale gas boom because of the technology constraints and more substantial costs.

H2. The number of oil rigs in the U.S., on the other side, will also have an impact on the crude oil price since the shale gas boom. The effect is negligible before the shale gas boom since OPEC was the absolute leading producers back then.

In the next section, we will discuss the empirical methods to test these hypotheses.

5. Econometric framework

5.1 Vector Autoregression

Vector autoregression (VAR) model is a stochastic process to capture the linear interdependencies among multiple stationary time series by incorporating own lagged values, the lagged values of the other model variables, and an error term. VAR modeling does not require as much knowledge about the forces influencing a variable as do structural models with simultaneous equations. The only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally. Following Sims (1980), given N stationary variables, a p lagged vector autoregression $VAR(p)$ system can be defined as:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{3}$$

where ε_t are the vectors of independently and identically distributed disturbances and Ω is the covariance matrix. For a covariance stationary $VAR(p)$ 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. [2]

5.2 Variance decomposition matrix (VDM) and various connectedness

To investigate the forward-looking relationship among all variables, we use the methodology of connectedness developed by Diebold and Yilmaz (2009, 2012, 2014, 2015, henceforth D&Y). The basic component of D&Y model is the generalized variance decomposition of forecast errors of variables, p lagged covariance stationary vector auto-regression $VAR(p)$ approximating model. The variance decomposition (or impulse responses) allows splitting the *H*-step ahead forecast error of each variable into parts that can be attributable to the various shocks. The aggregation of these decompositions will be subsequently used to compute the directional connectedness from a variable to any or all the included variable.

The variance decompositions computation is usually done by using orthogonal VAR shocks. The Cholesky identification scheme achieves orthogonality but the computed variance decompositions are then unstable, and they are dependent on the ordering of the markets. Thus, Cholesky decomposition is not suitable. A framework that produces invariant decompositions is

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[2] 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.

the generalized VAR that allows for correlated shocks but accounts for them appropriately. The framework, which we denote KPPS, has been first proposed by Koop, Pesaran, & Potter, (1996) and Pesaran & Shin (1998). The KPPS forecast error variance decomposition matrix (VDM) for *H*-step ahead is computed as

$$\theta_{ij}^{g}\left(H\right)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'h_h\Omega e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'h_h\Omega e_j\right)} \tag{5}$$

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.

The connectedness horizon H is crucial because it helps to analyze the connectedness in "short-run" and "long run." Consider a pairwise connectedness example, shocks to j many impacts the forecast error variance of i only with a lag, such that $C_{i\leftarrow j}$ may be small for small H but more significant for larger H. Intuitively, as the horizon lengthens there may be more chances for connectedness to appear and H approaches to infinity, it gives an unconditional variance decomposition. We use $H=10$ weeks in our primary analysis but also provide results with different H sequences.

5.3 Pairwise directional connectedness

Pairwise directional connectedness provides the information about the relative importance of each random innovation to the variables in the VAR. To get a unit sum of each row of the VDM, (information corresponding to the size of endogenous and exogenous shocks on a given variable), we can normalize each entry with its corresponding row as:

$$\tilde{\theta}_{ij}^{g}\left(H\right)=\frac{\theta_{ij}^{g}\left(H\right)}{\sum_{j=1}^{N}\theta_{ij}^{g}\left(H\right)} \tag{6}$$

which implies the row sum for any i^{th} variable to be $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)=1$, hence row sums across all the variable be $\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)=N$.

Now each element of the row-wise standardized VDM i.e. $\tilde{\theta}_{ij}^{g}(H)$ can be interpreted as the pairwise directional connectedness from variable j to variable i at horizon H. For the intuitive purpose, $C_{i\leftarrow j}(H)$ represents the pairwise connectedness from variable j to variable i at the horizon H and the opposite direction pairwise connectedness from a variable as $C_{j\leftarrow i}(H)$. The net pairwise directional connectedness then can be defined as

$$C_{ij} = C_{i\leftarrow j}(H) - C_{j\leftarrow i}(H) \tag{7}$$

5.4 Net-pairwise directional connectedness

The net pairwise directional connectedness identifies the dominant variable who transmit the information. Note that $C_{ij} = -C_{ji}$ and if $C_{ij} > 0$ then, economy j transmits the information to the economy i.

To find how all the variable are jointly contributing to a single variable, then the partial aggregation of connectedness from all variable to variable i except itself can be denoted as the row sum

$$C_{i\leftarrow\bullet}(H) = \frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{N} \tag{8}$$

Similarly, to compute how a market i is contributing to the shocks of all another variable (except by itself) by aggregating partially as

$$C_{\bullet\leftarrow i}(H) = \frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{i=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N} \tag{9}$$

5.5 Net-directional connectedness and total connectedness

Then the net directional connectedness can be measured as

$$C_{i}(H) = C_{i\leftarrow\bullet}(H) - C_{\bullet\leftarrow i}(H) \tag{10}$$

The total aggregation of the variance decompositions across all markets measures the system-wide connectedness. The total connectedness in all markets can be computed as

$$C(H)=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N} \tag{11}$$

5.6 Sample connectedness

The static, unconditional connectedness can be expressed as $C(x,H,A(L))$ because the connectedness C depends upon the set of variables x whose connectedness is to be examined, the predictive horizon H for variance decompositions, and the dynamics $A(L)$. Since, $A(L)$ is unknown in reality but can be approximated using a finite ordered vector autoregression $M(L;\theta)$ -which is a dynamic approximating model with a finite dimensional parameter θ. Allow for time-varying connectedness can equip analysis to capture evolution that may arise in the economy from changing tastes, technologies, institutions, business cycles, abrupt financial market environments (e.g., crisis, non-crisis) (Diebold & Yilmaz, 2014). Such time-varying connectedness can be expressed as $C_t(x,H,A_t(L),M(L;\theta_t))$. Because of finite samples of the observed data sample, we can only estimate approximating models, so we express the sample estimated connectedness as $\hat{C}_t(x,H,A_t(L),M(L_t^*;\hat{\theta}_t))$ where the data sample runs from $t=1,\ldots,T$ and L_t^* is the optimum lag selection using some information criterion for approximating VAR model for each data sample. We use the Akaike Information Criterion to select the optimum lag for approximating VAR and allow 4 lags as the maximum lags. For this purpose, we use 60 months rolling window to perform the analysis and later facilitate several different rolling window periods for analysis.

6. Empirical Results

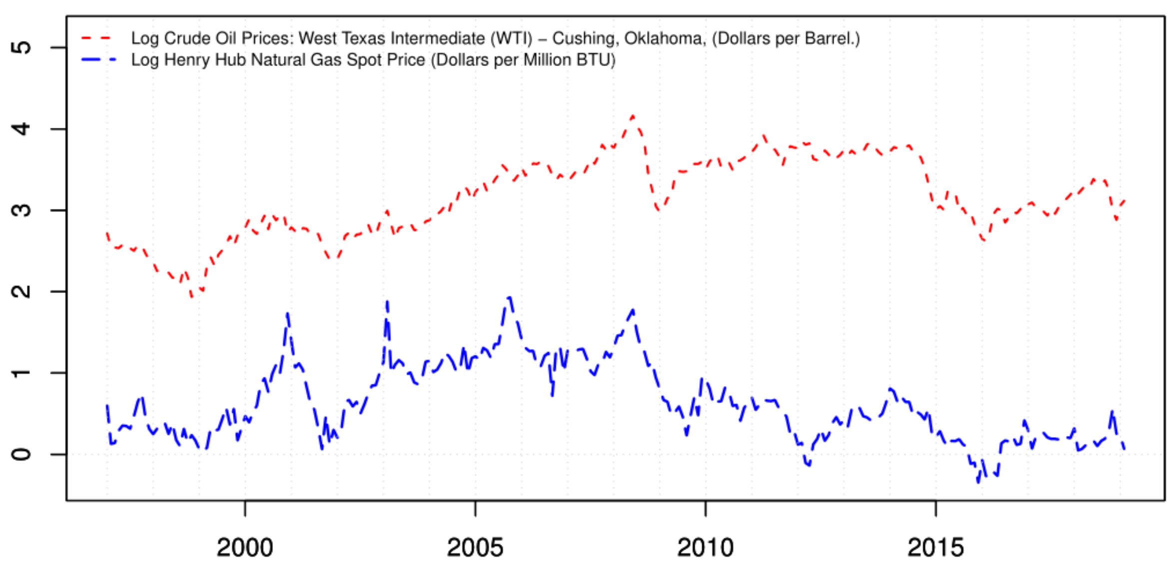
6.1 Data

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 producer's 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.

6.2 Descriptive Statistics

Figure 1 exhibits the trends of the log of CPI adjusted oil and natural gas prices. Post-2014, we the log of real oil prices ranges in between 2 to 4 suggesting within the range of 20 dollars to 55 dollars 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.

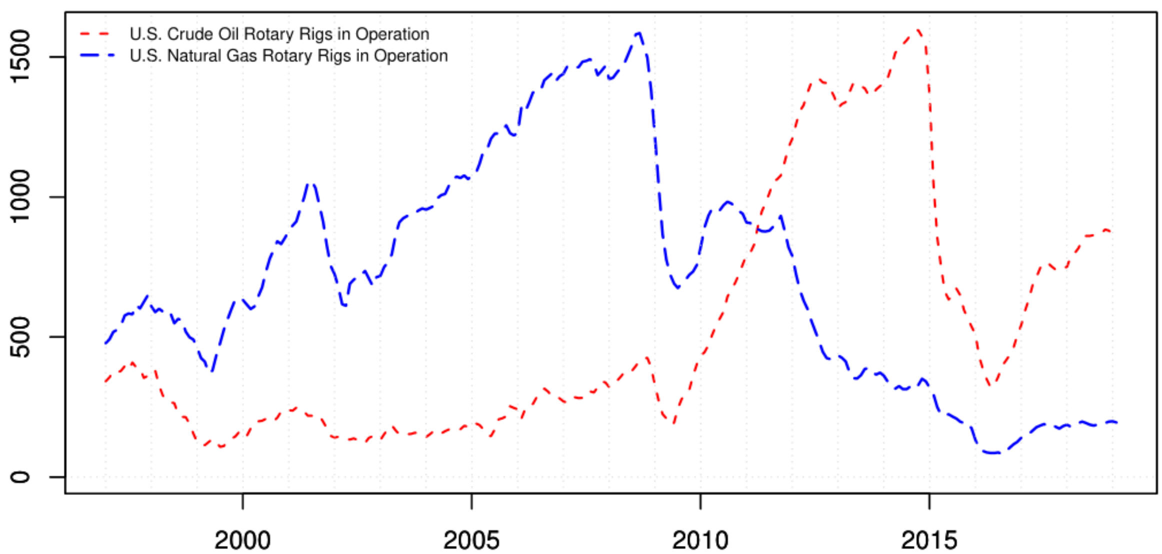
Figure 1: Trend of Oil and gas prices from 1997-01-31 to 2019-02-28



[Insert Figure 1 here]

Figure 2 exhibits the trend of numbers of rotary rig counts. 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. It is the recent period, since 2005, the rig counts are volatile, which coincide with our hypothesis that after the shale gas boom (which starts around 2007 see Appendix A1.), U.S. regional production starts to respond actively to the changes of the market energy price.

Figure 2: Trend of rig in operation from 1997-01-31 to 2019-02-28



[Insert Figure 2 here]

Table 1 shows summary statistics for a growth rate of gas rigs in operation (GR), growth rates of the oil rig in operation (OR), growth rates of CPI adjusted crude oil (ROP) and growth rates of natural gas prices (RGP) respectively.

Table-1: Descriptive Statistics of returns series

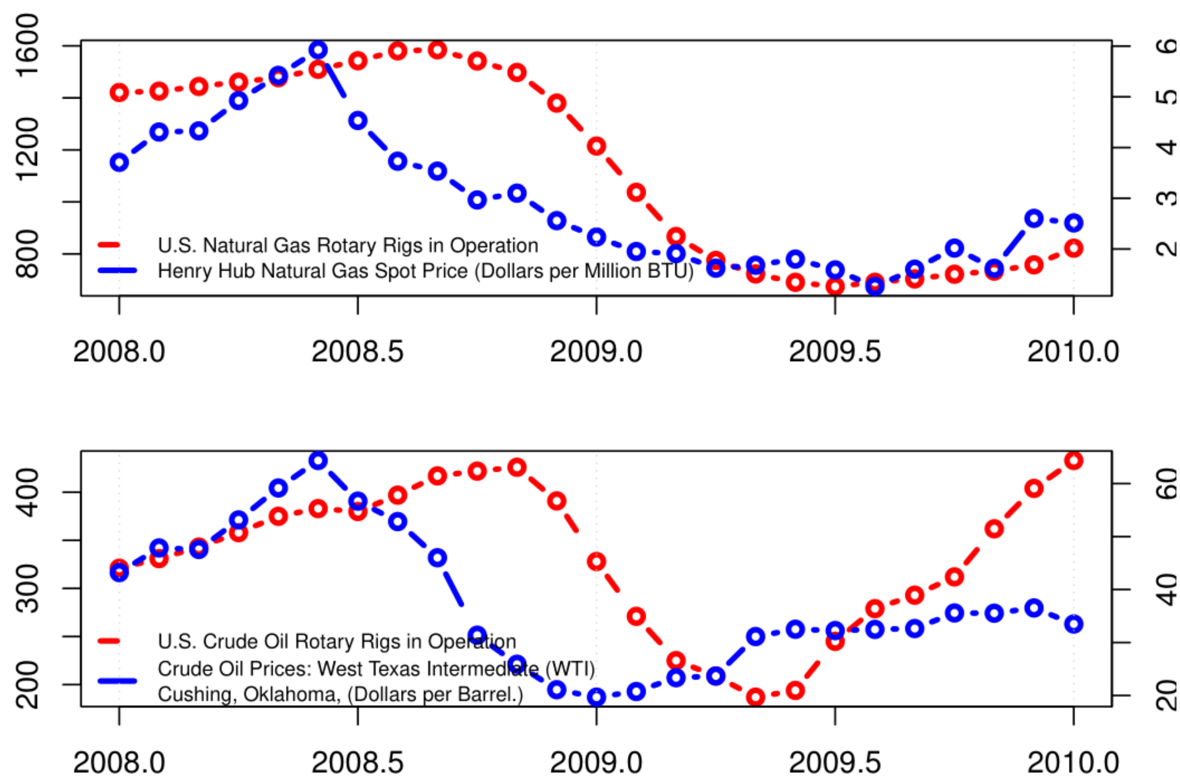
	Mean	Median	Max	Min	Std dev	Skew	Kurt	JB-test	ADF-test
GR	-0.002	0.005	0.154	-0.236	0.052	-1.157	6.392	116.908	-5.843
OR	0.006	0.010	0.263	-0.229	0.071	-0.182	4.492	21.472	-4.550
ROP	0.006	0.007	0.353	-0.318	0.094	0.062	3.926	8.970	-7.095
RGP	0.013	0.005	1.106	-0.586	0.181	1.382	8.994	481.194	-6.301

[Insert Table 1 here]

7. Empirical Results

The level series are well known to contaminated by the unit-root process. Therefore, we calculate the growth rates for all the variables (see Appendix A2 for unit root tests). Our analysis comprises of the sample connectedness. Each sample comprises of 60-month fixed period rolling window. For each sample, we fit an $VAR(L)$ as approximating VAR model for each data sample where L is 4 lags and performed variance decomposition, we choose H as the horizon of the 3 months.

Figure 3: Prices and rigs during 2008-2010 period



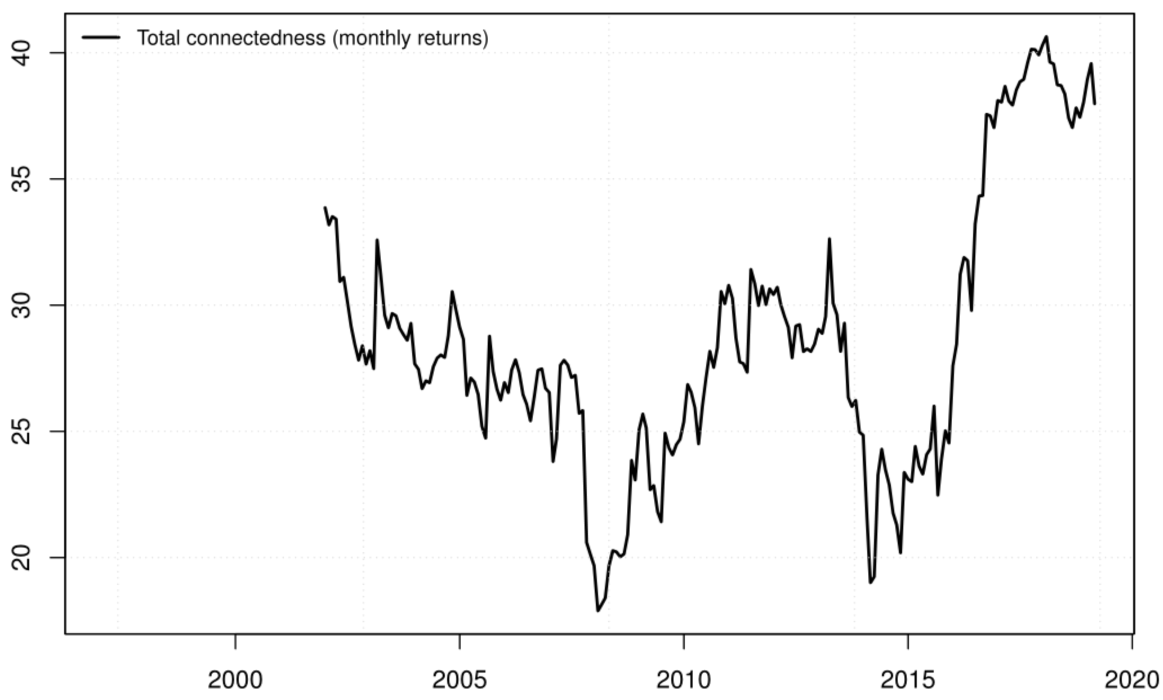
[Insert Figure 3 here]

The reason for such choice of H is visually supported by the plots of price and rigs given in Figure 3. To take an extreme case, we consider the 2008-2010 period of the financial crisis. As the financial crisis hit the market during mid of 2008, the prices of oil and gas reacted promptly and fell sharply, while the US regional producers took about 3-4 months period to act upon such price fall hence the rig counts started to fall only after 3-4 months. The rig counts follow approximately 3-4 months lags to the prices, therefore assuming any changes in the price, we would like to see how the producers behave.

7.2 Total Connectedness

The Granger causality shows historical evidence of how the value of a variable is affected by its own past or the past of some other variables. Compare to Granger causality, our interest in this research is to understand the connectedness of risks/information/shocks for a future period. This is also known as variance decomposition. The total aggregation of the variance decompositions for H period across all variables measures the H period forward-looking system-wide connectedness of risks/information/shocks. Putting this in simple words, variance decomposition shows the sources or decomposition of variance for any variable. The values of the Diebold and Yilmaz connectedness index which is based on the variance decomposition ranges between 0-100%. In a comparison of smaller values of Diebold and Yilmaz connectedness index, a higher value represents the variables in the VAR system is more connected, or the information/risk/shock transmissions across the variables are relatively higher.

Figure-4: 60 Weeks fixed window rolling sample for H=3



[Insert Figure 4 here]

Figure 4 shows the total connectedness of the variables implementing the Diebold and Yilmaz method of H-period ahead Generalized forecast error decomposition on 60 months fixed window

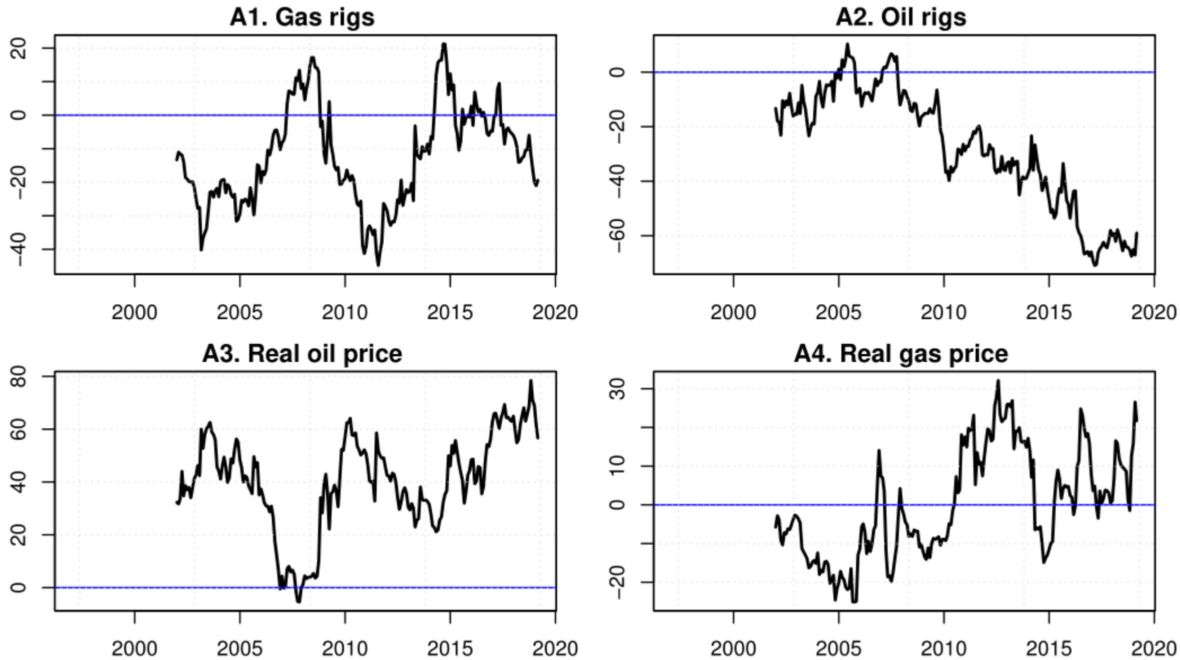
VAR system. The total connectedness answers how these variables are related to each other over time. We observe the total connectedness declines and hit bottom on January 2008, then rises until March 2013, then plunges to hit another bottom until February 2014. And Post 2014, the total connected rises sharply and stabilizes since October 2016. Post-2005 is known as the Shale boom period, 2007/8 suffered a financial crisis and in 2014 oil market collapses. As the total connected rises after the oil market crisis of 2014, it suggests the prices and rigs are more connected, and they are affecting each other more compared to previous periods. However, this might suggest either prices are influencing rigs (U.S. producers' behavior) or the other way. To investigate more, in the next section we present the analysis of net connectedness and net information spillover.

7.3 Net Connectedness and net information spillover

The net connectedness can be more interesting compared to the total connectedness. Since the total connectedness only answer how the variables are connected in an aggregated sense but the net connectedness answers how each variable relates to the rest variables; is a variable receiving risk or information from other variables or is it transmitting information to other variables. When the net connectedness is negative, then the variable is receiving net information from the remaining variables of the VAR system. While when the net connectedness indicator is positive, it shows its strength to influence other variables. The positive value indicates its power to spillover risk or information.

Considering for 3 months period forecast horizon considering 60 months fixed rolling window *VAR* models, the Panel A1, A2, A3 and A4 of Figure 6 show the net connectedness of the total gas rigs in operation, the total oil rigs in operation, the real oil price, and the real gas price, respectively. From Figure 7, it is evident that oil price is the one that spillovers information to the other variables. The information spillover from oil price to other variables is much stronger in recent years, especially after May 2007. Post-2011, the gas price on average is also transferring information rather than receiving information. However, the magnitude is much smaller. The net connectedness of the total number of gas rigs and oil rigs in operation is negative most of the time, suggesting that the number of gas and oil rigs receives information from other variables most of the time. However, for the total number of oil rigs in operation, the net connectedness is negative but much more significant in magnitude, especially from the beginning of the shale boom period of 2005.

Figure-5: 60 Weeks fixed window rolling sample for H=3, Net Transmission



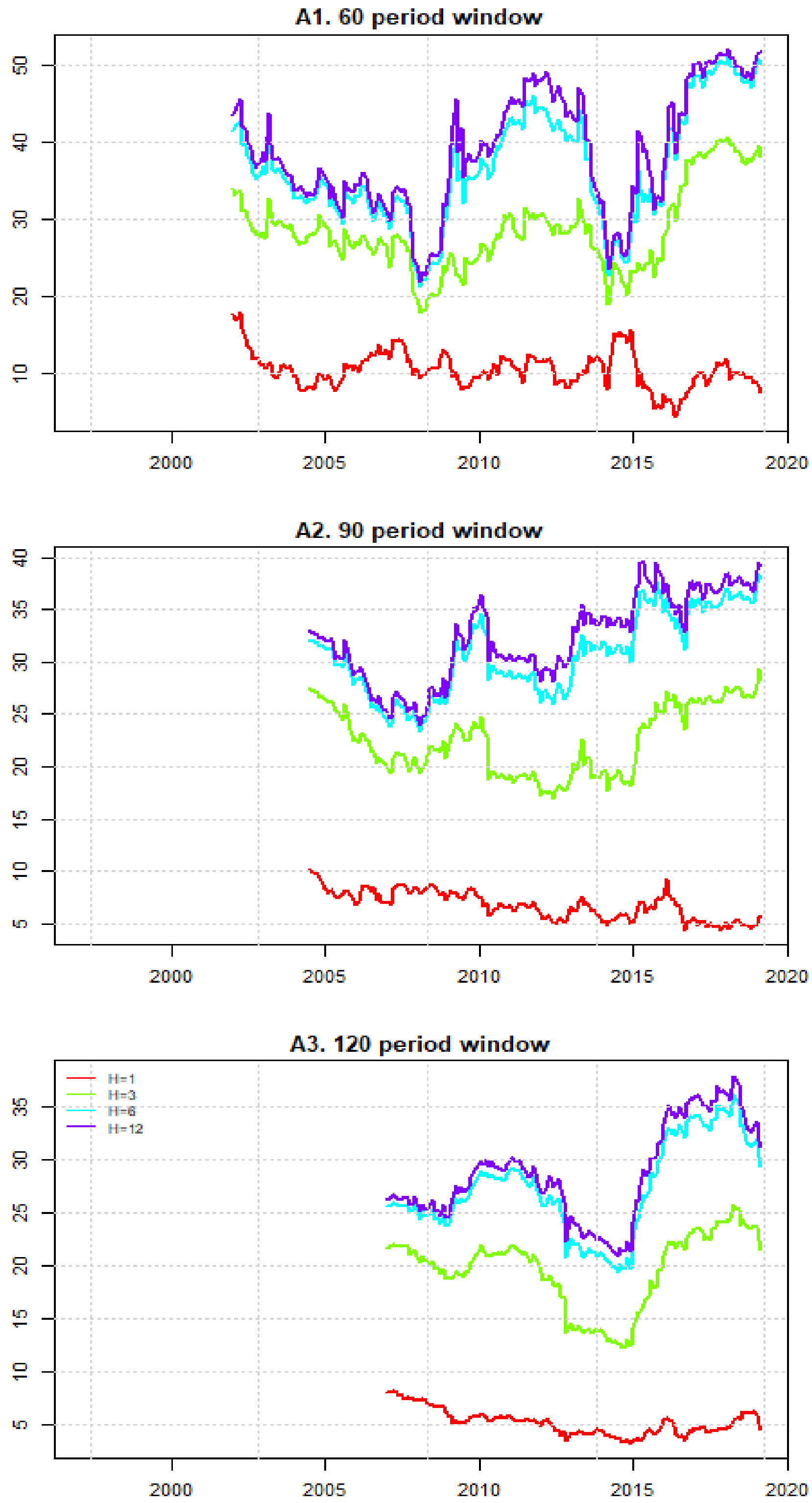
[Insert Figure 7 here]

When combing with the above information, the number of oil rigs counts after 2005 is mainly driven by the oil price. This further verifies the Hypothesis 1 in Section 2. However, looking forward to using the variance decomposition test, we didn't find support evidence for Hypothesis 2 that the rig counts transfer information to the oil price. This makes regional producers more susceptible to prices.

8. Robustness analysis

For the robustness, we run 12 different models. However, the results remain unchanged to show total connectedness increases sharply post 2014 period. We run various $VAR\left(L_t^*\right)$ with different fixed rolling windows of sizes 60, 90 and 120 months with the forecast horizon of 1, 3, 6, 12 months. Figure 6 exhibits the results. We find that the information transmission is more pronounced for a forecast horizon of three months period compared to one month, but such is not practically different post 6 months. This corroborates with our choice and argument to use the three-month period horizon for primary analysis presented in the previous section.

Figure 6. Total connectedness (window of 60 weeks and horizon of 3 weeks)



[Insert Figure 6 here]

8. Conclusion

In this paper, we investigate the Shale Band theory in the U.S. energy market. We test two main hypotheses. First based on a simple Cournot model, we hypothesize that changes in price will have an impact on the number of oil rigs in the U.S. However, this impact is weaker before the shale gas boom because of the technology constraints and more significant costs. Secondly, we hypothesis that the number of oil rigs in the U.S., on the other side, will also have an impact on the crude oil price since the shale gas boom. The effect is negligible before the shale gas boom since OPEC was the absolute leading producers back then. We think testing these hypotheses can be interesting to understand how U.S. oil and gas producer's response mainly after shale boom; does the firm position of US regional producer who operates in free-market setting threatens OPEC producers and to provide econometric estimation and validation of "Shale Band" theory.

Using monthly data on oil prices, gas prices, oil, and gas rig in operation, we implement a D&Y model to measure total connectedness and net connectedness. The D&Y approach is based on the variance decomposition which shows the sources or decomposition of variance of the variable from a VAR system. A higher value represents the variables in the VAR system is more connected, or the information/risk/shock transmissions across the variables are relatively higher. We find two exciting findings based on the D&Y total connectedness measure. First is that overall connectedness declines and hit bottom on January 2008, then rises until March 2013, then plunges to hit another bottom until February 2014. And Post 2014, the total connected rises sharply and stabilizes since October 2016. Secondly, we find these the total connected rises after the oil market crisis of 2014, it suggests the prices and rigs are more connected, and they are affecting each other more compared to previous periods. However, this might indicate either prices are influencing rigs (U.S. producers' behavior) or the other way. To investigate more, with D&Y net connectedness measures. We find that the number of oil rigs counts after 2005 is mainly driven by the oil price. This verifies our first hypothesis that changes in oil price have an impact on the number of oil rigs in the U.S. However, this impact is weaker before the shale gas boom because of the technology constraints and more substantial costs. However, we do not find the support of our second hypothesis that the rig counts transfer information to the oil price. This makes regional producers more susceptible to the prices changes. Therefore, the concept of Shale-Band theory is partially correct.

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Appendix

A1. Shale oil and tight gas production in the U.S.

A2. Augmented Dickey Fuller Unit Root test.