Impact of Shale Revolution on Crude Oil and Natural Gas Prices*

Shishir Shakya†
Bingxin Li‡
Xiaoli Etienne§

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Abstract

The shale technology advancements, such as horizontal drilling and hydraulic fracturing, have changed the dynamics of prices and drilling activities in the oil and gas industry in the past decade. Using variance decomposition from a reduced-form VAR model, we document that the crude oil and natural gas markets are more connected since 2012. The information spillover from oil returns to changes in gas exploration and field development, measured by the number of oil and gas rig counts, have increased dramatically and changes in rig counts positively respond to oil returns. On the other hand, changes in oil and gas rig counts also transmit more information to oil returns since the shale revolution with oil returns respond to them negatively, but only at marginal significance.

Keywords: Shale Revolution, Oil price, Gas price, Rig counts

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†Shippensburg University, 1871 Old Main Drive, Shippensburg, PA 17257; E-mail: sshakya@ship.com

‡Bingxin Li, John Chambers College of Business and Economics and Center for Innovation in Gas Research and Utilization (CIGRU), West Virginia University, Morgantown, WV 26506; E-mail: bingxin.li@mail.wvu.edu.

§Xiaoli Etienne, Davis College of Agriculture, Natural Resources and Design & Reginal Research Institute (RRI), West Virginia University, Morgantown, WV 26506; E-mail: xletienne@mail.wvu.edu.

1 Introduction

Over the past two decades, an important innovation in the energy industry 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 (Trembath et al., 2012). This has triggered a major increase in unconventional oil and gas production in the U.S. Between 2008 (***why 2008***) and 2019, the total natural gas and oil produced in the U.S. increased more than XXX and XXX, respectively (U.S. Energy Information Administration (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, the U.S. has surpassed Saudi Arabia and Russia as the top oil producer in the world and has become the world's largest producer of natural gas (EIA, XXXX).

The shale boom is often cited as a significant 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 after 2010 the projected natural gas prices in the U.S. with only supply shocks, 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 declines 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 technological innovation and investment in the energy sector were driven primarily by its high-profit margin, particularly before the 2008 financial crisis when oil and natural gas prices hit record highs. Recent research discusses how higher prices stimulate investment in the U.S. onshore drilling industry (Kellogg, 2011, 2014). 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 production cost. Kellogg (2014), for instance, uses a dynamic model to show that the oil company's 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 ###This does not seem right, please check.### and decreased vice versa. Such a theory is very important because the oil and gas industry has a relatively high sunken cost or an 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 volatility. Kellogg (2014) finds the empirical estimates show significant responses of drilling activities to price volatility, being consistent with the theoretical prediction.

In this paper, we investigate the relationship between exploration/investment activities and energy prices, focusing on oil and natural gas industries in the U.S. 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. Hence, we 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." 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. Kellogg (2011) shows that drilling operations appear to follow prices with a three-month lag. The rig counts data, which are periodically published by EIA, are frequently referred to by journalists, economists, security analysts, and government officials, and are included in many industry statistical reports.

Several papers have analyzed the behavior of crude oil and natural gas prices. However, only a few studies focus on the study of oil or gas regarding the rig counts. Khalifa et al. (2017)

documents a non-linear impact of changes in oil prices on rig counts and 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 (Osmundsen et al., 2008, 2010); 2) how exploration and investment activities in the oil industry respond to different economic conditions (Fattouh et al., 2016); 3) how oil price changes affect rig activities (Kellogg, 2014).

The present paper extends the literature by looking at the information spillover between energy prices and rig counts in the U.S., namely crude oil and natural gas, and how these relationships have evolved 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 (2017) argues that the investment decisions may respond to price fluctuations somewhat differently. For instance, the investment horizon of unconventional oil and gas is typically much shorter, and the productivity declines over time of unconventional oil and gas production. Indeed, Baumeister and Kilian (2016) compares the 2014-16 episode with the large, sustained oil price decline in 1986-87 and suggests that oil investment spending has become less responsive to oil price changes during the recent tight oil boom. ***Is this the case for our results?***No. However, our results compare before and after the shale boom, not 2014-16 with 1986-87.*** Examining the information spillover in the oil and gas industry, we find that crude oil returns transmit much more information to crude oil and gas rig counts since the shale boom. While the opposite information flow, from changes in crude oil and natural gas rig counts to crude oil returns, is not as pronounced. Our findings support that crude oil returns are net information spillover and lead the information flow in the oil and gas industry.

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 U.S. 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 2, we provide a brief theoretical framework. Section 3 explains the empirical methods. Section 4 explains the data and summary statistics. Section 5 reports the main results and discuss its implication, and Section 6 concludes.

2 Theoretical Framework

This section provides a simple game-theoretic setting on how oil and gas producers behave upon the structural changes led by the shale boom in the U.S. and the resulting changes in oil and gas prices and rig counts. 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 a positive initial setup cost K when entering the industry in stage one. 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 other firms' decisions. The equilibrium condition with J^* firms in the market can be defined as

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

where π_{J^*} (π_{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 loss of generality, we further assume that each firm is able to produce oil at a constant marginal cost, $c \to 0$.

Assume the following simple inverse demand function of oil,

$$p(Q) = a - bQ \tag{2}$$

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

$$\underset{q_i}{Max} \ (p(q_i + q_{-i}) * q_i) \tag{3}$$

where $Q \equiv q_i + q_{-i}$. Solving for the first-order condition of equation (3) and let $q_i^* = \frac{Q^*}{J}$, we obtain

$$p'(Q^*)\frac{Q^*}{J} + p(Q^*) = 0 \tag{4}$$

Combining equations (2) and (4), we obtain the equilibrium market output and clearing price:

$$Q^* = \frac{aJ}{J+1} \quad and \quad p^* = \frac{a}{J+1} \tag{5}$$

The profit of each firm is:

$$\pi_{J^*} = \left(\frac{a}{J^*+1}\right)^2 \tag{6}$$

The equilibrium number of the entrants J^* gives

$$J^* = \frac{a}{\sqrt{K}} - 1 \tag{7}$$

Based on equations (5), (6), and (7), the equilibrium oil price falls and the production quantity increases as the number of firms increases. Also, as $J \to \infty$, the price approaches the competitive market equilibrium, and each firm makes zero economic profits. Further, equation (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 drilling and exploration costs. In recent years, especially since the shale revolution in the past decade, 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. EIA (2017) ### Shishir, pls change this to U.S. EIA (2017)### estimates that the reduction in drilling and exploration costs can be as high as XXXX%. Here, we simply assume the setup cost before the shale gas boom, $\overline{K}$, is higher than that after the shale boom, which is denoted as $\underline{K}$.

Before the shale boom, with a high entry cost, $\overline{K}$, as suggested by equation (7), there were only a limited number of supermajors in the oil and gas industry, for example, the consortium of Seven Sisters in the U.S. 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 world's oil production (according to EIA), is a consortium of 13 countries and the single largest entity influencing the world's 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 monopolists. The monopoly equilibrium quantity and price are

$$Q_m^* = \frac{a}{2} \quad and \quad p_m^* = \frac{a}{2} \tag{8}$$

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 newly entered firms compete in the market for prices and profits; however, they do not have enough capacity to satisfy the market's entire demand. 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 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 with the same limited capacity, k. Let the lowest and highest price of the range be $\underline{p}$ and $\overline{p}$. Suppose one firm chooses a price that 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

$$k\underline{p} = (a - k - \overline{p})\,\overline{p} \tag{9}$$

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

$$\underline{p} = \frac{1}{k}\left(\frac{a-k}{2}\right)^2 \tag{10}$$

$$\underline{\pi} = \overline{\pi}\left(\frac{a-k}{2}\right)^2 \quad (11)$$

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. In comparison, the firm with a higher capacity will act at a higher price range. This justifies the shale band concept in the U.S. oil market in the past decade that oil prices fluctuate within a price range. [1]

Before 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, or the unconventional investments, with new technologies and lower costs generally have more constrained capacities than the major conventional 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 according to the changes in setup costs, global demand, firm capacity, and market prices. The aggregate oil market price fluctuates within the range in response to the changes in the number of firms, global demand, and firm capacity. Therefore, all else equal, we would expect a mutual impact with lags between the changes in the number of rigs and shale oil/gas prices after the shale gas boom.

However, the hypothesis implied by the model should be interpreted with caution. Given the complex investment decisions and various driving forces of price dynamics, the relationship between changes in price and changes in the number of rig counts might not be as straightforward in the data, especially when using the number of rig counts to represent the firm's drilling activities. For example, Khalifa et al. (2017) find the impact of changes in oil prices on rig counts is non-linear, and Black and LaFrance (1998) claim that the relationship between changes in oil prices and rig counts may not be that obvious and direct due to the presence of the lagged response. In addition, the traditional rig count methods focus on the oil- or gas-targeted rigs.

[1] Shale band concept was first introduced by Olivier Jakob, the director of Petromatrix, a consultancy based in Switzerland. It states that the oil price movements after the shale boom are within a certain range (the band).

According to an EIA 2013 report, there were more than 50% of new wells produced both oil and natural gas since 2011.[2] Therefore we should take into accounts for integrated production of natural gas and crude oil.

3 Empirical Methods

To estimate the relationship between rig counts and oil/natural gas prices, we use a reduced-form vector autoregression model with $p-$lags, $VAR(p)$. The $VAR(p)$ model captures the linear interdependencies among multiple time series by incorporating their own lagged values, the lagged values of the other variables, and an error term.

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t \tag{12}$$

where X_t represents the system of N endogenous variables. In the present analysis, X_t is a column vector, $[oil\ return,\ oil\ rig\ count,\ gas\ return,\ gas\ rig\ count]'$. ε_t is a vector of independently and identically distributed disturbance, Ω is the covariance matrix, and P is the number of lags of the variables.

For a covariance stationary process there exists the moving averages representation, $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, 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 provide 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. An impulse response is the reaction of any dynamic system in response to some external change and describes the system's reaction as a function of time (or possibly as a function of some other independent variable) that parameterizes the system's dynamic behavior. The forecast error variance decomposition is a transformed version of impulse response functions ### in what sense? expand...###.

We next construct information spillover indices for the four time-series, i.e., how much information can be extracted from one variable when forecasting another variable, following the work by Diebold and Yilmaz (2009, 2011, 2012, 2014, 2015) (DY henceforth). The DY

[2] https://www.eia.gov/todayinenergy/detail.php?id=13571/

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 attributed to its shocks and shocks from other variables. Hence, it indicates the amount of information each variable contributes to the variation of other variables from 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 and 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,

$$\theta_{ij}^{g}\left(H\right)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e'_{i}h_{h}\Omega e_{j}\right)^{2}}{\sum_{h=0}^{H-1}\left(e'_{i}h_{h}\Omega e_{j}\right)} \tag{13}$$

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. #h$_h$?#

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 summing the row entries to obtain the directional spillover index from variable j to i at forecast horizon H, denoted as $C_{i\leftarrow j}\left(H\right)$,

$$C_{i\leftarrow j}\left(H\right)=\tilde{\theta}_{ij}^{g}\left(H\right)=\frac{\theta_{ij}^{g}\left(H\right)}{\sum_{j=1}^{N}\theta_{ij}^{g}\left(H\right)}\times 100 \tag{14}$$

Equations (14) implies the row entry for any i^{th} variable is $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)=1$, and the sum across all row variables equals N, i.e, $\sum_{j=1}^{N}\tilde{\theta}_{j}^{g}\left(H\right)=N$. Similarly, $C_{j\leftarrow i}\left(H\right)$ denotes the pairwise 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 $C_{ij}\left(H\right)=C_{i\leftarrow j}\left(H\right)-C_{j\leftarrow i}\left(H\right)$, can be used to determine which variable is the information transmitter, e.g., $C_{ij}\left(H\right)>0$, and which variable is the information receiver, e.g., $C_{ij}\left(H\right)<0$.

Additional connectedness indices can be constructed to evaluate the role of each variable in the overall information transmission system. Equations (15), (16), and (17) 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,

$$C_{i\leftarrow\bullet}\left(H\right)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}\times 100=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}{N}\times 100 \tag{15}$$

$$C_{\bullet\leftarrow i}\left(H\right)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}\left(H\right)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}\times 100=\frac{\sum_{i=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}\left(H\right)}{N}\times 100 \tag{16}$$

$$C_{i}\left(H\right)=C_{i\leftarrow\bullet}\left(H\right)-C_{\bullet\leftarrow i}\left(H\right) \tag{17}$$

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

$$C\left(H\right)=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}\left(H\right)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}\left(H\right)}{N} \tag{18}$$

The forecast horizon H is of interest because it helps analyze the connectedness in short- and long-runs. For instance, shocks to j may only affect the forecast error variance with one lag, such that $C_{j\leftarrow i}\left(H\right)$ may be low at immediate horizons but increase as we move to more distant horizons. Diebold and Yilmaz (2014) suggest taking precaution while considering the selection of forecast horizon. For example, risk managers who use daily data would consider $H = 10$ to cohere with the 10-day value at risk (VaR) required under the Basel accord. In contrast, portfolio managers should link H to the rebalancing period.

In our analysis, we focus on two forecast horizons, three months and six months. Previous literature reports that a 3-6 month lag exists in the oil and gas industry. In these industries, to drill a well, producers first have to issue a request for quotation (RFQ) from drillers. Once drillers are awarded the contracts, the drillers' crew install the rig and start the extraction of reserves. Therefore the changes in prices of oil or gas affect only the producers and not the driller; a lagged relationship between the effect of prices and rig count should be observed in the data.

Black and 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 geo-engineering principles. Similarly, Khalifa et al. (2017) empirically verified that the impact of oil prices on rig counts is up to one quarter lagged. They use quantile regression and quantile-on-quantile models to verify a non-linear relationship between oil price and rig counts. Still, 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 changes in oil wells productivity, rig efficiency, drilling costs, commodity inflation, hedging, and inventories (Hunt and Ninomiya, 2003).

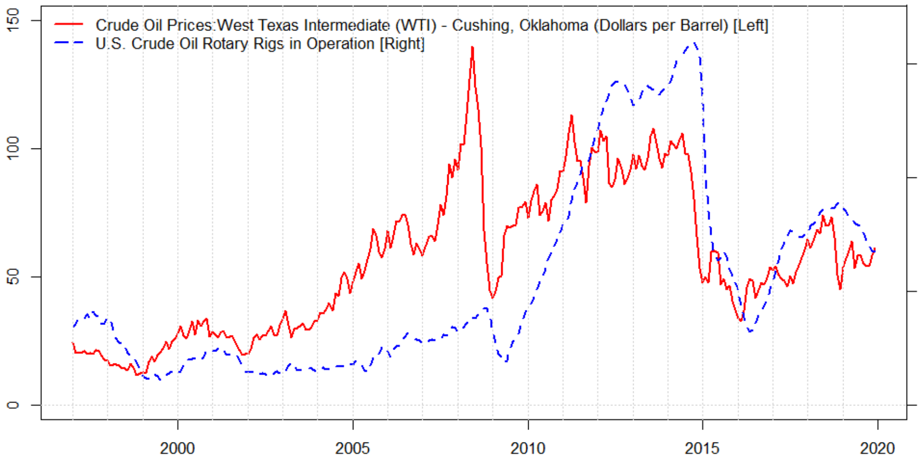
Additionally, since one of our main hypotheses is that the information contained in the rig count and energy price may have evolved over time, we hence construct time-varying connectedness indices to capture evolution that may have occurred due to changes in the underlying economy and business cycles, improvement in drilling and exploration technologies, shifts in energy policies and regulations, and development in financial market environments. We use the rolling-window approach, with 90 months being the main window size, to construct the time-varying connectedness indices within the system.

4 Data

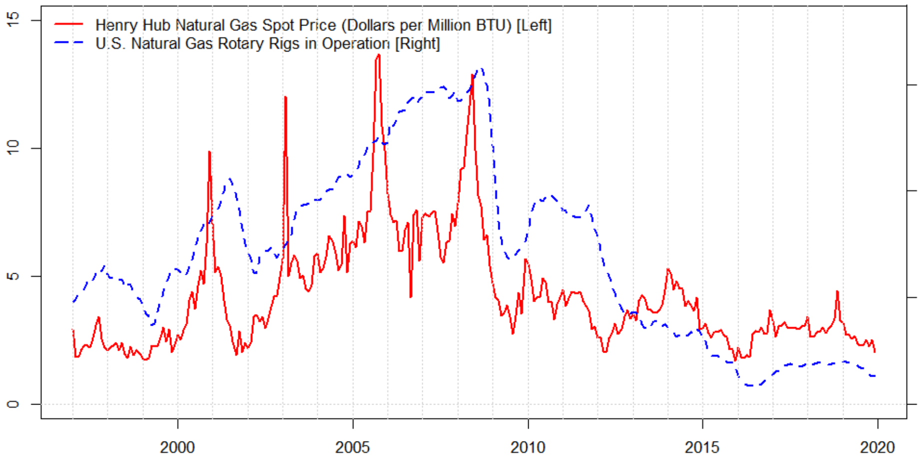
We use West Texas Intermediate (WTI) crude oil spot price (dollars per Barrel) and the U.S. crude oil rotary rig in operation as a proxy for the activities of regional oil producers. To control for the possible effects of the shale gas, we use the Henry Hub natural gas spot price (dollars per million BTU) and the U.S natural gas rotary rig in operation as a proxy for regional shale gas producers' activities. The crude oil price, natural gas price, and CPI index are downloaded from Federal Reserve Economic Data (FRED). We retrieve the U.S. crude oil rotary rigs in operation and the U.S. natural gas rotary rigs in operation from the U.S. EIA database and label them as Oil Rig Count (ORC) and Gas Rig Count (GRC), respectively. The monthly data is from January 1997 to December 2019.### Why start in 1997?###[3]

[3] We use monthly data in our study rather than weekly. The choice of data frequency depends on the number of lags between prices and rig counts. On average, there were 3-6 months of lags between prices and rig counts. If we have considered weekly data, then a nearly 12-24 weeks lag (3-6 months lag) is needed to incorporate in our VAR model. For a VAR model with k variables and p lags of each variable, in each equation it requires to estimate $\left(p + kp^2\right)$ parameters. Therefore, even in the lower bound with $k = 4$, we need to estimate $12 + 4 \times 12^2 = 580$ parameters.

Figure 1: Trend Diagram, January 1997 - December 2019, Monthly



(a)



(b)

Figure 1 plots the time series of nominal prices and rig counts for crude oil and natural gas. We observe clear changes in trends around 2009. Panel (A) of Figure 1 plots the trends of WTI crude oil price per barrel (left y-axis) along with the numbers of crude oil rotary rig in operation (right-axis). The nominal crude oil price run-up quickly from 2000 to 2008 and reached the highest, \$147.02 per barrel, on July 11, 2008. Followed the price decline during the 2008-2009 financial crisis, it gradually bounced back and reached a relatively flatter range between \$85 to \$135 per barrel from 2011 to 2014. Meanwhile, Chinese economic growth slowed after 2010. While fracking boosted North American oil production sharply and Saudi Arabia kept its production stable, low oil prices offered more of a long-term benefit than giving up market share, leading to a sharper decline of oil price in 2014 (Depersio, 2020). After 2014, the crude oil price fluctuated around the range between $30 to $75 per barrel. This period is consistent with the Shale-band theory that oil prices fluctuate within a range due to the technological changes and shale gas boom.

The number of U.S. crude oil rotary rigs in operation increased dramatically since 2010, reached the highest in 2015. Then followed a sharp decline, it bounced back from the beginning of 2016. From Panel A of Figure 1, the number of crude oil rigs after 2009 followed a similar pattern as crude oil prices, however, with a few months lag.

Panel (B) of Figure 1 shows the trend of the Henry Hub natural gas spot price (left y-axis) along with the number of natural gas rotary rigs in operation (left x-axis). Natural gas prices were much more volatile in the first half of the sample before 2009. After 2009, natural gas prices became relatively low and persist. It fluctuated within a range of $1.73 to $6 per Million Btu. The number of U.S. natural gas rotary rigs in operation gradually decreased since 2009. Same as in the crude oil market, the number of natural gas rigs shares a similar trend as natural gas prices, however, it lags the price for a few months. The numbers of oil rigs and gas rigs have similar patterns since 2015.

Table 1: Summary Statistics, January 1997-December 2019

	Panel A. Level						
Variable	Summary statistics				Correlation matrix		
	Mean	Std dev	JB-test	ADF-test	Oil price	Oil rig count	Gas price
Oil price ($/barrel)	26.18	11.86	15.60***	-1.99	1		
Oil rig count	537.12	426.55	52.85***	-2.10	0.55****	1	
Gas price ($/mmBTU)	2.09	1.14	195.24***	-3.16	0.29****	-0.38****	1
Gas rig count	701.44	419.10	14.65***	-1.68	0.33****	-0.44****	0.76****
	Panel B. First Difference (in log)						
Variable	Summary statistics				Correlation matrix		
	Mean	Std dev	JB-test	ADF-test	Oil return	ΔOil rig count	Gas return
Oil return	0.60	0.09	9.63***	-7.26***	1		
ΔOil rig count	0.50	0.07	24.24***	-4.59***	-0.06	1	
Gas return	1.20	0.18	527.67***	-6.44***	0.13*	0.08	1
ΔGas rig count	-0.30	0.05	107.93***	-5.97***	0.03	0.30****	0.03

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

Table 1 reports the summary statistics and correlation coefficients for the crude oil and natural gas prices and their corresponding rig counts. In Panel A we report the CPI-adjusted prices and numbers of rigs in operation. On average, the number of rigs in operation for crude oil is smaller than for natural gas. However, the oil rig count shows more variations than the gas rig count.

The Augmented Dickey-Fuller (ADF) tests show that when considered all four variables in their levels, they are non-stationary. By contrast, their corresponding growth rates, calculated by the first differences in the logarithmic form are all stationary. Therefore we report the summary statistics of the percent growth rates of the variables in Panel B and label them as Oil Returns (OR) and Gas Returns (GR), respectively.[4] Panel B of Table 1 shows that the natural gas returns are higher than crude oil returns and the natural gas market is much more volatile than the crude oil market.

From Table 1, we also observe that oil price is, on average, positively correlated with both the numbers of rigs in operation and natural gas prices. Natural gas prices, by contrast, are negatively correlated with oil rig counts. Meanwhile, the two rig count variables are also negatively correlated. The return variables show a significantly lower level of correlation. Interestingly, crude oil returns/changes in oil rig count are positively correlated with natural gas returns/changes in gas rig count, implying the inherent connection between these two markets.

5 Empirical Results

For the rest of the analysis, we therefore use all variables specified in their first differences. Based on the Akaike Information Criterion (AIC), five lags are included in the VAR model. In addition, to account for seasonality, we also include several exogenous variables to account for the macroeconomic effects. These variables include the TED Spread (TEDRATE), SP 500 Index, and Trade Weighted U.S. Dollar Index against major currencies, all from the Federal Reserve Bank of St. Louis. We first report empirical results from the full sample analysis, then focus on the dynamic results from the rolling window analysis.

5.1 Full Sample Analysis

In this section, we present the Granger-causality test (Table 2), the cumulative response function (Figure 2), and the full sample total-connectedness (Table 3) results as follows.

We first perform the Granger causality test to determine whether one series is capable of forecasting another. Table 2 shows the F-values of the Granger causality tests. The null hypothesis is that the variables in the left column of the table do not Granger cause the variables

[4] For the rest of the paper, we use oil/gas return and Δoil/gas price interchangeably.

Table 2: Granger Causality Tests based on the *VAR* Model, January 1997 - December 2019

Null hypothesis	Oil return	ΔOil rig count	Gas return	ΔGas rig count
Oil return $\nrightarrow$ variables in top row	1.62	9.09***	2.38	2.44
ΔOil rig count $\nrightarrow$ variables in top row	1.20	58.00***	0.01	4.18**
Gas return $\nrightarrow$ variables in top row	0.78	1.26	13.74***	0.13
ΔGas rig count $\nrightarrow$ variables in top row	0.78	5.97**	1.89	85.35***

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

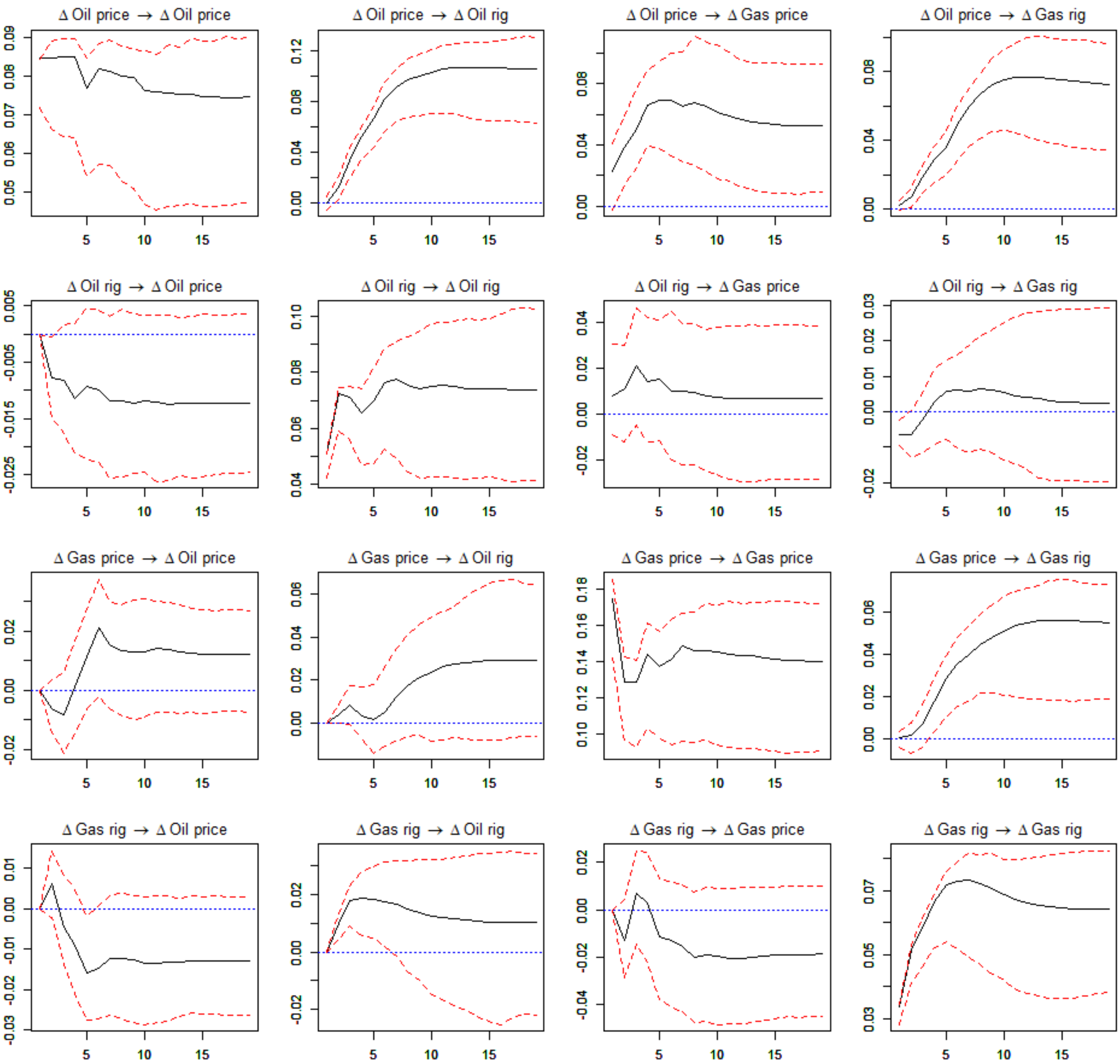
on the top row of the table. From Table 2, we reject the null hypothesis that crude oil returns do not Granger cause crude oil rig counts, suggesting that oil returns help predict changes in oil rig counts. It is different for natural gas returns which can not reject the null hypothesis that they do not Granger cause the natural gas rig counts. Expect for its own lags, none of the other three variables Granger causes natural gas returns. Meanwhile, there exists bi-directional causality between crude oil rig counts and natural gas rig counts. In other words, the lagged rig counts in one market help predict the rig counts in the other market.

Figure 2 plots the cumulative impulse responses of the variables of interest to one standard deviation increase in another variable, as well as their corresponding 90% confidence intervals for the whole sample. Changes in oil rig counts respond positively to oil returns, suggesting that oil exploration and investment activities are sensitive to oil price changes. The positive response grows fast between one month to ten months, afterwards, it plateaus. We observe similar patterns of gas returns and gas rig counts in response to oil returns, except that the positive responses of oil return to gas returns maximized around five months and gradually decrease afterward.

On the other hand, the responses of oil returns to oil rig counts are mostly negative and not significant. Oil returns appear to only respond significantly to a shock originated from itself. Similarly, we find that natural gas rig counts positively respond to an increase in natural gas returns, and this effect is statistically significant, starting from the fourth month. The natural gas returns do not respond significantly to a shock in natural gas rig counts.

Figure 2 also suggests that the oil rig counts positively respond to gas rig counts, but this effect is only limited to the first six months after the shock occurred. For gas rigs, interestingly, it responds negatively in the first two months after a shock in oil rig counts, and positively but non-significant in the remaining months. In sum, the crude oil returns seem to have a first-order impact on the rest three variables, and oil and gas rig operation activities seem to connect with

Figure 2: Cumulative Impulse Response Function



Notes: Each cumulative response is 18-period long with one standard deviation shock and 90% confidence interval and is based on the VAR model that uses monthly data from January 1997 to December 2019, with 5-period lags selected using Akaike Information Criterion (AIC). Seasonal dummy variables and exogenous variables are included in the analysis.

each.

Table 3 reports the total connectedness measured on the VAR model. As discussed in Section 3, we present results for two forecast horizons, $H = 3$ months and $H = 6$ months, in panels A and B, respectively. Overall, the total connectedness among the four variances is 15.49% at the three-month forecast horizon, which increases to 22.53% at the six-month forecast horizon. Results show that the most variance of forecast error in crude oil and natural gas returns can be explained by their own variations (over 90% for both commodities). These

Table 3: Connectedness

To \ From	Oil return	ΔOil rig count	Gas return	ΔGas rig count	Contrib. from others $C_{i\leftarrow\bullet}(H)$
			Panel A. $H = 3$ months		
Oil return	94.14	0.96	1.68	2.23	*4.86*
ΔOil rig count	22.26	72.65	1.33	3.76	*27.35*
Gas return	3.29	0.64	94.40	1.66	*5.60*
ΔGas rig count	13.19	4.19	6.75	75.87	*24.13*
Contrib. to others $C_{i\rightarrow\bullet}(H)$	*38.74*	*5.79*	*9.75*	*7.65*	**total-connectedness**
Net: $C_i(H) = C_{i\leftarrow\bullet}(H) - C_{i\rightarrow\bullet}(H)$	***33.89***	***-21.56***	***4.15***	***-16.48***	$C(H) =$***15.49***
			Panel B. $H = 6$ months		
Oil return	91.54	1.02	4.59	2.84	*8.46*
ΔOil rig count	30.17	64.06	2.49	3.28	*35.94*
Gas return	3.32	0.71	93.73	2.24	*6.27*
ΔGas rig count	23.22	3.65	12.57	60.56	*39.44*
Contrib. to others $C_{i\rightarrow\bullet}(H)$	*56.71*	*5.38*	*19.66*	*8.36*	**total-connectedness**
Net: $C_i(H) = C_{i\leftarrow\bullet}(H) - C_{i\rightarrow\bullet}(H)$	***48.25***	***-30.56***	***13.39***	***-31.08***	$C(H) =$***22.53***

Notes: Each cell represents the contribution of the column variable in explaining the forecast variance of the row variable. $C_{i\rightarrow\bullet}(H)$ represents the % of information variable i contributes to other variables. $C_{i\leftarrow\bullet}(H)$ represents % of total information contributed by others recieved by i. $C_i(H)$ is the net-connectedness. $C(H)$ shows the total-connectedness which is sum of all net-connectedness.

percentages are slightly lower at the six-month horizon. However, the declines are minimal (from 94.14 to 91.54 for oil, and from 94.4 to 93.73 for natural gas), suggesting that oil and natural gas returns are mostly driven by factors influencing their own market, independent of rig counts and other markets.

For crude oil rig count, although its past values drive the majority of its change, innovations from crude oil returns, natural gas returns, and natural gas rig counts contribute 30.17%, 2.49%, and 3.28%, respectively, of its forecast error variances at the six-month horizon. Similar patterns are found for natural gas rig counts, where about 40% of the information comes from the other three variables. However, it is interesting to note that the contribution of oil return innovations to natural gas rig count, e.g., 23.22% at the six-month horizon, is almost twice as much as those from natural gas returns, e.g., 12.57% at the six-month horizon, implying that the crude oil return transfers more information to gas rig counts than natural gas return. Crude oil returns have a first-order impact on the other three variables, Other than their own past values.

The connectedness results in Table 3 further suggest that crude oil returns are the biggest information transmitter of the four variables considered, followed by natural gas returns, and the two rig count numbers. This result is consistent with the role of crude oil prices play in the overall macroeconomy. The difference between the connectedness "to" and "from" other variables gives the net directional spillover index for each variable, indicating each variable's contribution to overall returns and rig counts. On average, crude oil and natural gas returns are net information transmitter, while the two rig counts are net information receiver. The amount of information received and transmitted increased at the six-month horizon than that at a three-month horizon for all variables considered.

The overall level of connectedness we found in this paper is smaller compare to other studies. For example, Scarcioffolo and Etienne (2019) study the connectedness in the U.S. regional natural gas markets in the post-deregulation era and find 50%, 65%, and 70% of overall connectedness at 1-day, 5-day, and 20-day horizons. Antonakakis (2012) finds a total spillover of 46.0% and 31.3% among exchange rates before and after the introduction of the Euro at the 10-day horizons. Awartani and Maghyereh (2013) shows an overall connectedness of 27.1% and 19.5% at the 10-week horizon for the return and volatility spillover of oil prices and equities in the Middle-East, respectively. Kang et al. (2017) suggests that gold, silver, crude oil, wheat, and rice have a total-connectedness of 33.3% at the 10-week horizon. The previous study either considered the prices for homogeneous goods (Scarcioffolo and Etienne, 2019; Awartani and Maghyereh, 2013) or different commodities (Kang et al., 2017; Diebold et al., 2017) that may present different connectedness due to regulations, fundamental factors, and other market-specific drivers. Our study is based on a mixture of variables–oil and natural gas prices, and rig counts of oil and gas are homogeneous within but heterogeneous across each other. Furthermore, producers may be promptly responsive to prices while the driller may not because of binding contracts between producers and drillers.

5.2 Rolling Sample Analysis

The oil and gas markets have undergone tremendous volatility during our sample period due to various structural breaks or progressive changes. It is reasonable to assume that market integration and the shock transmitting mechanism may have evolved depending on the specific market conditions. Therefore, we employ a rolling-window approach to account for time-varying relationships and re-estimate the connectedness among oil returns, oil rig counts, gas returns, and gas rig counts. Compared to the conventional approach in the literature that imposes a discrete structural break in the data, the rolling-window method not only accounts for abrupt, sudden changes occurred in the market, uncover patterns and cycles in the evolution of market integration (if any), but also allows for progressive, slowly-evolving developments due to technology advances, changes in consumer preferences (Scarcioffolo and Etienne, 2019).

Figure 3: Total Connectedness

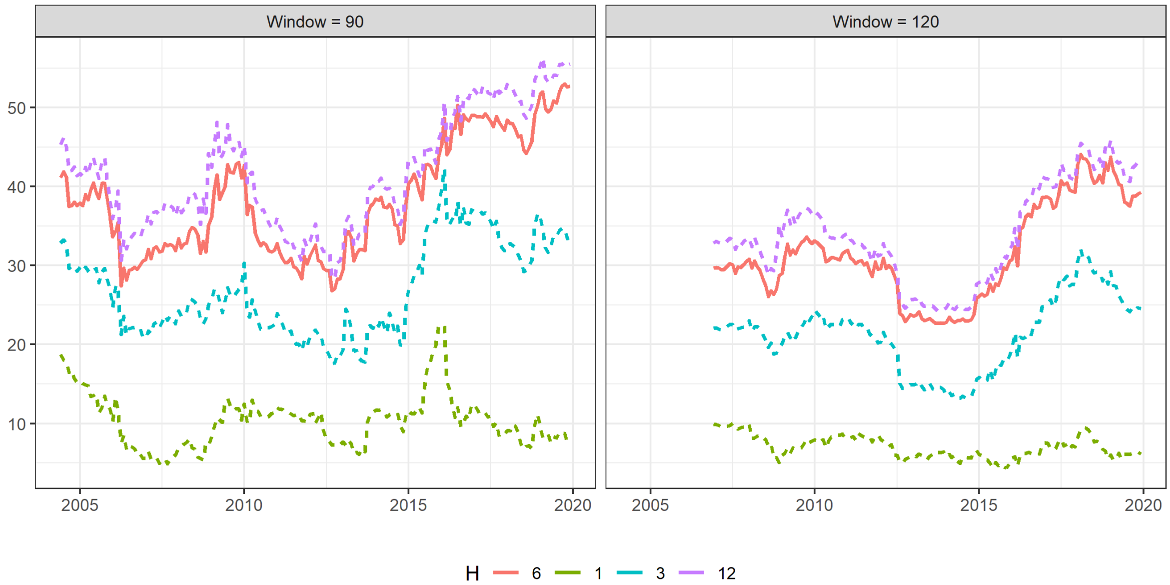


Figure 3 plots the time-varying total-connectedness when the window sizes are 90 and 120 months.[5] One caveat of using the rolling window to construct each connectedness index is that it should be interpreted as a measure of connectedness during the preceding 90 (or 120) months rather than the ending date alone. We focus on the total-connectedness with a horizon of $H = 6$ months, at the same time, the results with horizons of $H = 1$, 3, and 12 months is plotted for comparison.

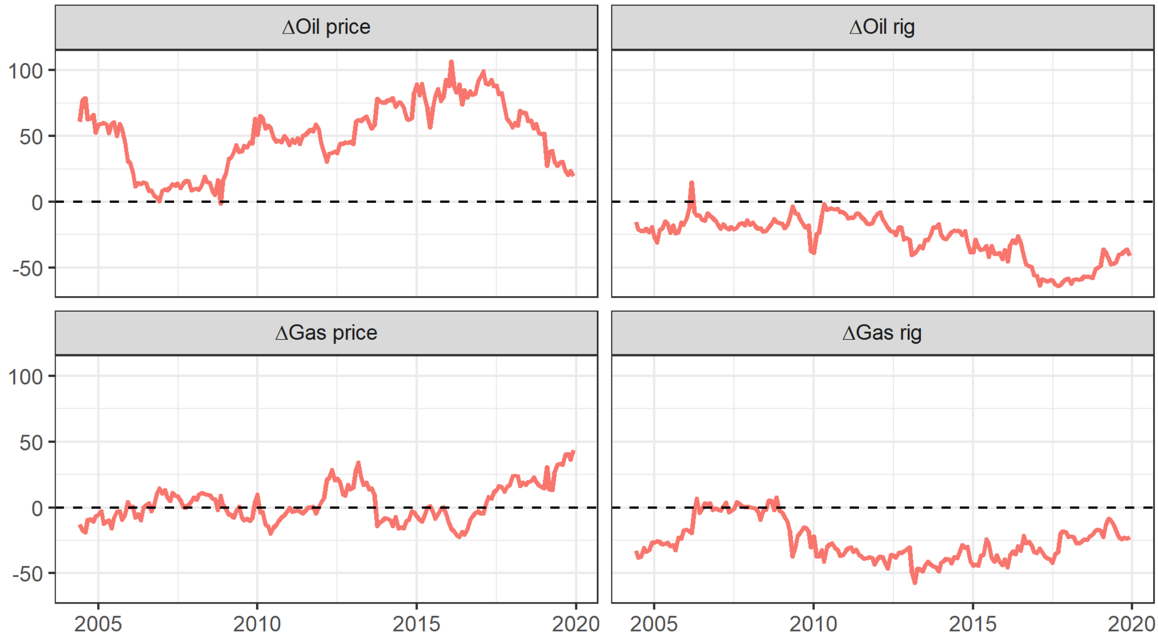
From Figure 3, the pattern of rolling total-connectedness index behaves similarly regardless of the window size. The total-connectedness indexes for horizons of one month and three months mostly fluctuate between 5 and 40 percent. The connectedness at six and twelve-month horizons are very close to each other, ranging between 30 and 55 percent for most of the sample period.

The total connectedness has overall increased over the sample period. However, the index appears to have been mostly trending downward before September 2012, after which it significantly increased. The evolution of the total connectedness index over the sample period suggests that the returns and rig counts of crude oil and natural gas are becoming more closely

[5]Our data is monthly from January 1997 till December of 2019 (276 observations) and there is a lag of 3-6 months in the oil and gas industry to respond to information. Let's consider $k = 4$ variables (oil returns, oil rig counts, gas returns, and gas rig counts) and $p = 4$ lags, then VAR model requires to estimate $\left(4 + 4 \times 4^2\right) = 68$ parameters. Analysis of VAR with a rolling window below 68 months can be noisy; see Figure 3. For this reason, we analyze the rolling window sample of more than 68 month periods.

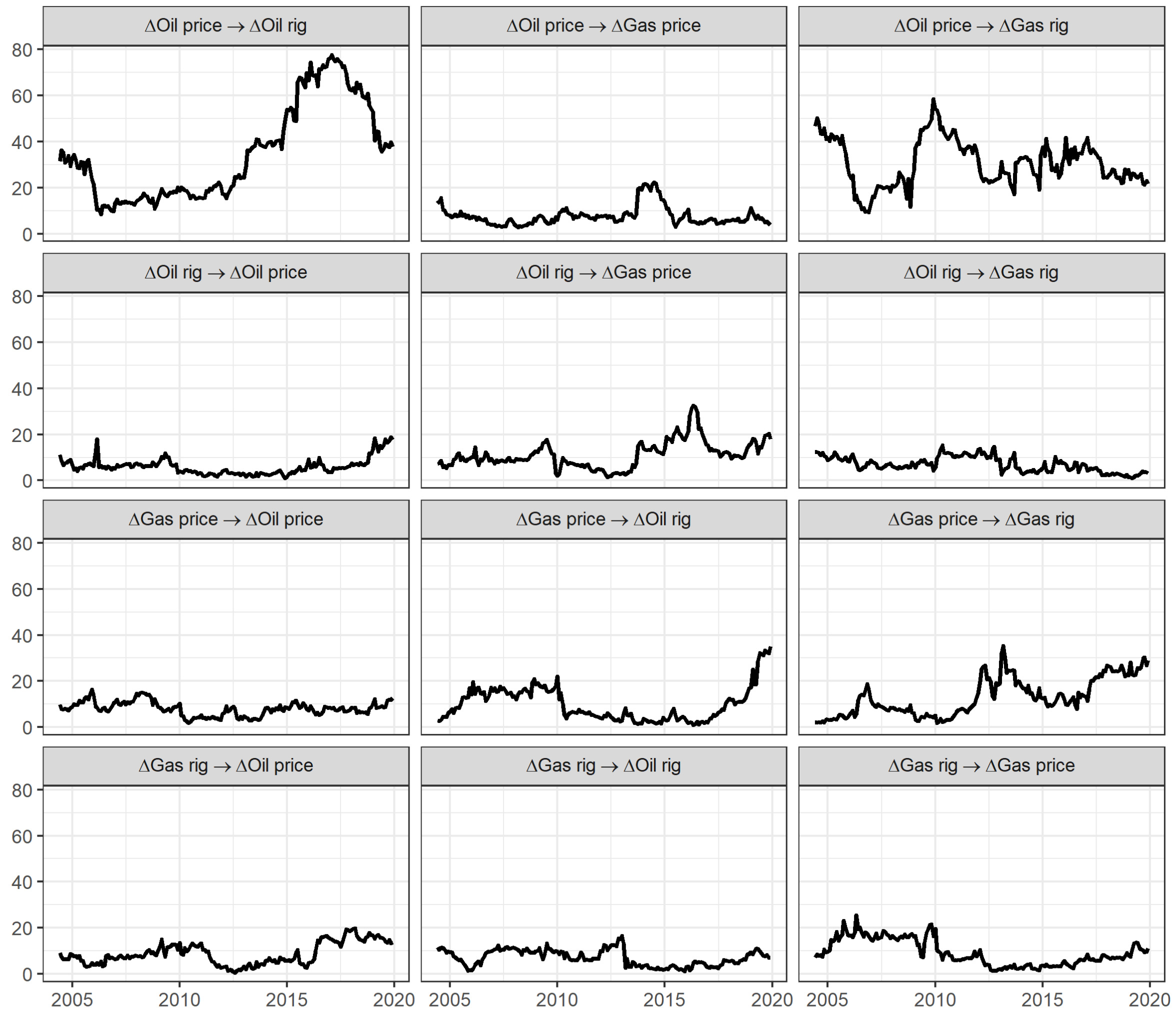
linked after 2012. In the 90 (or 120) months preceding September 2012, unconventional shale gas and tight oil production rose, leading to a narrower gap between gas consumption and domestic production, and more intensified competition between domestic producers. The more competitive oil and gas markets have facilitated information transmission between the returns and rig counts, resulting in a higher connectedness index (Scarcioffolo and Etienne, 2019).

Figure 4: Net Spillover (Rolling Window of 90 Months and Horizon of 6 Months)



From the analysis above, the results with different rolling windows and horizons are robust. Simultaneously, as discussed in Section 3, a rolling window of 90 months and a horizon of six months are reasonable given our sample and data. For the rest of the analysis, we report results only for a rolling window of 90 months and a horizon of six months to save space. Figure 4 presents the rolling-window analysis of the net spillover for each variable considered in the study. The top left panel exhibits crude oil returns are net-spillover, suggesting the response of remaining variables to oil returns. We note that post-2012, there is a rise of net-spillover from oil returns. This observation provides additional evidence of shale band theory, as regional producers adjust oil and gas productions in responding to oil prices. The top right panel of Figure 4 is for oil rig count and implies that it is a stable net-receiver of the information over time. The bottom left panel shows the net-spillover from the natural gas returns. Unlike oil, net-spillover from gas returns is less pronounced. It may indicate that regional producers are more susceptible to gas prices because gas is a domestic product that oil. The bottom right panel of Figure 4 shows that gas rig counts are net-receiver of information since 2009.

Figure 5: Pairwise Directional Connectedness (Rolling Window of 90 Months and Horizon of 6 Months)



Next, we show the sources of changes that determine the evolution of the spillover index. Figure 5 plots the pairwise directional connectedness index with a rolling window of 90 months and a horizon of six months. The pairwise directional connectedness shows how much information flows from one variable to the other. From the top row of Figure 5, oil returns clearly spillover to oil rig counts and gas rig counts, while little information is transmitted to gas returns. However, the dynamics of the connectedness indexes from oil return to changes in oil rig and gas rig are different. For example, information transmission from oil returns to changes in oil rig count consistently increased since 2012 and reached the highest, about 76%, around

2017. While the connected index from oil returns to changes in gas rig count reached the highest, about 60%, in 2010, and gradually declined to a relatively stable level between 20% to 40%. This may be due to the different driving forces for price changes during these periods, as discussed in Section 4, which in turn conveys different information content to the oil and gas markets. Oil rig counts and gas rig counts do not seem to spillover much information to other variables, which is consistent with our previous findings that rig counts are mainly information receivers. However, it is interesting to point out that the connected index from changes in oil rig count to gas returns and that from changes in gas rig count to oil returns both moderately increased after 2012, implying the integration over time between these two markets. However, there exists little information spillover between the two rig count numbers. We also observe that gas returns spillovers information to changes in gas rig count after 2012.

The observation from Figure 5 is critical because it confirms our hypothesis in Section 2 that since the shale revolution the drilling activities in both the oil and gas industry, measured by rig counts, are more responsive to oil returns. It also echoes the findings in Table 2 and Figure 4 that oil returns have a dominating impact to lead the information flow in these two markets. However, the evidence of information transmission from rig counts to prices is not significant as we expected in the model. We also observe dynamic changes of the connected index from changes in oil and gas rig count to oil returns after 2012, however, the changes are not as dramatic as those from oil returns to oil/gas rig counts. This finding is consistent with the impulse response function documented in Figure 3, where Oil/gas returns negatively respond to changes of oil/gas rig counts, however, the response is not significant at 90% level.

As mentioned in Section 2, these results need to be interpreted with caution. Oil and gas rig counts as measures of oil and gas drilling activities and investment spending are not perfect. The lags between prices and rig counts in different markets and under different market conditions might vary and alter the dynamics of findings. There may be important features in the markets that our model and test could not untangle. However, the analysis is instructive in that the directional relationship between returns and changes in rig counts are robust for different tests.

6 Conclusion

In this paper, we apply a reduced-form $VAR(p)$ model which is based on the variance decomposition to investigate the dynamic changes in the relationship between prices and the number of rig counts in the crude oil and natural gas markets. We find that with the technology advancement and enhanced drilling efficiency since the shale boom, oil and gas exploration and field development activities, measured by changes in the number of rig counts, have been much more responsive to oil price changes. High oil returns lead to larger numbers of rig counts, therefore, more drilling activities. The crude oil price has a first-order impact on spillover information to the investment decisions and drilling activities in both the oil and gas industry.

The information flow from the changes in the number of oil and gas rig counts to oil returns also increased after the shale gas boom, however, the changes are not as pronounced as that from oil returns to changes in rig counts. Overall the numbers of oil and gas rigs are net information receivers. We document negative feedback from the number of oil/gas rig counts to oil prices that increased rig counts decrease crude oil returns. Although this relationship is not significant, it provides marginal evidence of the shale band theory.

Natural gas returns respond positively to crude oil returns. They spillover more information to changes in gas rig count after 2012. However, They do not seem to transmit information to crude oil markets. Although the crude oil and natural gas markets are inherently connected, the crude oil price has been net-spillover. We find that the changes in the number of gas rig counts transmit information to oil returns. This may because more new wells produced both oil and natural gas and production of natural gas and crude oil are more integrated since the shale boom.

Integration between the oil and gas markets is complicated given the price dynamics, varying production of the unconventional wells, and the different number of lags in each variable, which may beyond what our model and analysis could capture. This paper provides evidence among the directional information channels in these two markets, shedding light on prudent drilling or investment decisions at varying market conditions, especially with new technology development.

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