Shale Revolution, Oil and Gas Prices, and Drilling Activities in the United States

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Abstract

We investigate the interplay between energy prices and drilling activities in the United States and how this relationship has evolved in light of the shale revolution. Using connectedness indexes constructed on vector autoregressive models, we find that the linkage between exploration and drilling activities, measured by active rotary rigs in operation, and oil and gas prices in the US has strengthened since 2012. Oil prices played a dominant role in information transmission between drilling activities and energy prices. Since the mid-2010s, natural gas price variations have become an increasingly important channel through which external shocks affect the US energy sector. We further document that both the oil and gas industry's drilling activities have become more responsive to price variations during the shale revolution.

Keywords: Shale revolution, Oil price, Gas price, Rig count
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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 allowed producers to extract oil and gas from low-permeability reservoirs efficiently. Although neither of these techniques is new, a long history of private and government investment has led producers in the Barnett area to combine them in an economically feasible manner (Trembath et al., 2012). The resulting dramatic rise in unconventional oil and gas production has made the US one of the world's major energy producers.[1]

The shale revolution is often cited as a significant contributor to the sustained low natural gas prices in the US, and to a less extent, depressed global oil prices in recent years. For instance, Hausman and Kellogg (2015) estimate that the unprecedented supply expansion in 2007-2013 lowered wholesale natural gas prices in the US by $3.45 per million cubic feet (mcf). Wiggins and Etienne (2017) show that after 2010 the projected natural gas prices in the US with only supply shocks, most of which are related to shale production, aligns closely with the actual natural gas price behavior. Baumeister and Kilian (2015) estimated that as much as $16 of the $49 per barrel 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 US and the supply shocks in other countries.

A complementing view relating the shale revolution to energy prices is that the 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 high energy prices stimulated investment in the US onshore drilling industry (Kellogg, 2011, 2014). The high oil and gas prices in the early 2000s made the shale technology cost-competitive when it was

[1]In 2000, shale gas provided only 1% of US natural gas production; by 2010, it was over 20%, and in 2019 the US dry shale gas production was about 75% of total US dry natural gas production. See https://en.wikipedia.org/wiki/Shale$_{g}as$ and https://www.eia.gov/tools/faqs/faq.php?id=907t=8, accessed on November 27, 2020.

first introduced, stimulating further investment that led to massive productivity gains and lower production costs. Kellogg (2014), for instance, uses a real options framework to show that an oil company's investment behavior, which often incurs high and irreversible fixed costs, responds significantly to changes in oil price volatility, and the oil drilling behavior in Texas supports the theoretical prediction of this model. This aspect is particularly important for shale producers since unconventional wells are often more expensive to drill and complete, while in the meantime present lower production uncertainty than conventional wells (Newell et al., 2019).[2]

This paper investigates the relationship between exploration/investment activities and energy prices, focusing on the US's oil and natural gas industries during the shale revolution. Although various measures exist for oil and gas exploration and development activities (e.g., number of wells drilled, investment spending, etc.), these data are not publicly available, and even if they are, they often only exist for a shorter time period. Hence, we follow the literature (Apergis et al., 2016; Khalifa et al., 2017; Ringlund et al., 2008) and use rig counts to measure exploration activities and field development effort that took place in the oil and gas industry.

According to the Energy Information Administration (EIA), a rig is "a machine used for drilling wells that employ a rotating tube attached to a bit for boring holes through rock." The rig count refers to the number of "rigs drilling for crude oil, rigs drilling for natural gas, and other rigs drilling for miscellaneous purposes."[3] 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. Additionally, as rig counts indicate the actual activities carried out by oil and gas companies, they are often considered the barometer of the energy industry's performance and health, as well as the degree of investor confidence and the level of future energy output. The rig

[2] Newell et al. (2019) note that unconventional oil and gas producers have a great deal of control over the production levels since shale resources are uniformly distributed and easy to identify. By contrast, conventional oil and gas producers have to drill many dry holes in search of a few productive wells.

[3] See https://www.eia.gov/dnav/ng/TblDefs/ng_enr_drill_tbldef2.asp, accessed on October 16, 2020.

count data, which are periodically published by the EIA, are frequently referred to by journalists, economists, security analysts, and government officials and are included in many industry statistical reports.

Using connectedness indexes from a reduced-form vector autoregression model and data from 1997 to 2019, we document that the relationship between oil and gas prices and their active rotary rigs in operation in the US had strengthened, especially since 2012 when shale oil and gas started to take off. Oil prices are the most prominent information transmitter among the four variables during the sample time. Since the mid-2010s, natural gas price variations have become an increasingly important channel through which external shocks affect the US's energy sector. Drilling activities in both the oil and gas industry have become more responsive to price variations since the shale revolution. However, the information transmitted from oil prices to rig count had declined when oil prices were fluctuating in a relatively stable range toward the end of the sample period. In contrast, the information transmitted from gas prices to gas rig counts has increased during the same time frame.

Our paper contributes to the present literature in at least three ways. First, despite previous work (e.g., Newell et al., 2019; Mason and Roberts, 2018), the existing literature remains sparse on the effect of the shale revolution on oil and drilling gas activities, and the present paper aims to provide such information from an alternative, more aggregated perspective. Second, unlike previous studies that only focus on either the oil or gas industry separately, the present paper examines the interactions between rig counts and prices for both energy products. Energy firms often simultaneously invest in the petroleum and natural gas industries. Depending on their expected profits, firms' investment decisions would favor one over the other. Therefore, the rig count numbers measure the relative strength of investor confidence between the two sectors. Also, since oil wells often contain gas (i.e., associated gas), oil drilling activities could be partially driven by natural gas price variations (and vice versa). Thirdly, the present paper employs a time-varying rolling window approach to account for the effect of shale revolution on the information flow between prices and investment activities. Compared to previous studies that use a single structural break, the rolling window approach allows us to identify gradual and progressive changes over the sample period. Since the shale revolution is a gradual process that started in the early 2000s, using the rolling-window approach allows us to more accurately document how information flow between the drilling activities and price changes have changed during the sample period.

The remainder of the paper is organized as follows. In Section two, we provide a brief review of the literature and highlight our contributions. Section three explains the empirical methods. Data and estimation results are discussed in Sections four and five, respectively. The last section concludes the paper.

2 Background and A Brief Review of Literature

Two factors govern an energy firm's decision to explore and develop new oil/gas wells: the expected price it receives in the future and the mining technology (Lasky, 2016). A popular approach in the literature linking these factors is the real options framework, which models a firm's drilling decision as a function of price volatility and the cost of investment determined by the mining technology (e.g., Kellogg, 2014). In general, as the price uncertainty increases, the firm's drilling activity declines. Other studies attempt to model a firm's investing decisions by incorporating geological and engineering principles. For example, Black and LaFrance (1998) develop a theoretical model of oil supply from known reserves and the maximum efficient recovery (MER) rate, finding that the linkage between oil price changes and rig count may not be that obvious and direct due to the presence of the lagged response from geo-engineering principles.

Khalifa et al. (2017) summarize the existing literature, noting that the relationship between oil/gas prices and rig counts, and consequently the oil/gas supply, can be empirically analyzed through three dimensions: 1) how drilling speed and productivity change over business cycles and the resulting oil/gas price responses (Osmundsen et al., 2008, 2010); 2) how exploration and investment activities in the oil and gas industry respond to different economic conditions (Fattouh et al., 2016); and 3) how oil and gas price changes affect rig activities (Kellogg, 2014). This paper seeks to understand the bi-directional linkage between energy prices and rig counts, thus combining the first and third strands of the literature.

Of the existing papers that empirically examines the interplay between oil or gas prices and drilling/investment activities, Mohn and Osmundsen (2008) find that for the Norwegian Continental Shelf in 1965-2004, there exists a robust, long-term oil price effects on exploration activities; however, the short-term impact is weak. Khalifa et al. (2017) use quantile regression and quantile-on-quantile models to show a non-linear relationship between oil price and rig counts in the US. Such a non-linear relationship may exist because of the changes in oil well productivity, rig efficiency, drilling costs, commodity inflation, hedging activities, and inventories (Hunt and Ninomiya, 2003). Iliescu et al. (2018) show a long-run equilibrium between oil prices and rig count in the US when allowing structural breaks. However, they do not specify when such structural breaks occurred in the data. Using monthly data from 1997 to 2013 in the US, Brigida (2018) shows that a threshold relationship exists between rig count and natural gas prices. Specifically, when gas prices increase above \$6.74/mmBTU, changes in the rig count negatively affect prices, while gas prices do not affect subsequent drilling activities; by contrast, when prices are below the threshold, natural gas price changes positively affect rig count, while drilling activities do not affect gas prices.

Several recent papers estimate the elasticity of drilling activities in the oil and gas sectors. Ringlund et al. (2008) use data from 1987 to 2006 and analyze how oil rig activity responds to crude oil prices, finding that rig activity in the US reacts much faster and stronger to oil price fluctuations in the US than in other regions. They further note that the long-run elasticity of rig activity in the US is above 1.5. Using monthly data from 2007 to 2014. Hausman and Kellogg (2015) estimate that the short- and long-run drilling responses (for wells that are drilled and completed) in the natural gas industry to be 0.09

and 0.81, respectively.

The shale revolution has fundamentally changed many aspects of the US energy sector, and the relationship between oil/gas prices and drilling activities may be subject to such an impact. Compared to conventional oil and gas production, shale wells differ in several key ways. First, unconventional wells require a much higher initial investment as they need to be first drilled vertically and then horizontally. Conventional wells, on the other hand, only require the vertical segments. However, the average drilling and completion costs for unconventional wells have been steadily declining since 2012 due to improved wells designs, higher drilling efficiency, and better tools (EIA, 2016). Second, compared to conventional oil and gas investment, which often resemble high-risk/high-reward games, unconventional wells present a significantly lower level of productivity risk. Newell et al. (2019) note that shale resources are easy to identify because they tend to be uniformly distributed geographically, lowering the likelihood of dry holes.

Third, unconventional wells are able to produce a substantial amount of resources quickly. Newell et al. (2019) find that in their first full month of production, unconventional gas wells on average produced 2.3 times as much as conventional gas wells. Furthermore, Kleinberg et al. (2018) note that the annual decline of conventional oil well production amounts to 6% per year, while for unconventional wells, its production declines by 60% after the first year, followed by a 25% in the subsequent year. The high production decline rate of unconventional wells suggests that unconventional oil and gas has a shorter investment horizon. More wells need to be drilled to maintain or increase production when oil or gas price increases. Brown et al. (2019) show that the amount of oil and gas produced in the first year of new wells on a per rig basis, which they termed as the drilling productivity, has significantly increased since 2008, the period that largely coincides with the rise of unconventional oil and gas production.

Overall, the conventional wisdom suggests that unconventional oil and gas producers tend to be more price-sensitive than conventional producers due to shorter investment horizons, less uncertainty about well productivity, and a faster production rate. Gülen et al. (2013) analyze the production data from more than 16,000 wells drilled in the Barnett play and show that the economic viability of drilling new horizontal (unconventional) natural gas wells are highly sensitive to natural gas prices and well productivity. using data in Wyoming, Mason and Roberts (2018) confirm increased price responsiveness in the shale era — while the estimated price elasticity of drilling before 2003 was 0.44, in 2003-2014 it increased to 0.82. However, Newell et al. (2019) find that unconventional and conventional gas drilling has virtually the same price elasticity using data from Texas from 2000 to 2015. They further note that the increased price response of shale gas supply mainly stems from the higher productivity of unconventional wells.

In the oil sector, Apergis et al. (2016) analyze oil production in six main unconventional oil production regions in the US, finding that crude oil prices drive total oil production and rig count in the short-run and that there exist significant feedback effects between total oil production, rig count, and crude oil prices in some of the regions. Baumeister and Kilian (2016) compare the 2014-2016 episode with the large, sustained oil price decline in 1985-1987 and find that oil investment spending has become slightly more responsive to oil price changes during the recent tight oil boom — while oil prices in 2014-2016 fell twice as much as in 1985-1987, oil-related investment fell by 48% as compared to only 21% during the mid-1980 price decline.

Instead of estimating the elasticity of drilling activities, the present paper extends the literature by evaluating the information spillover between energy prices and rig counts in the US and how the spillover pattern has evolved in response to the shale revolution. We focus on information spillover for two reasons. Firstly, econometric models estimating price elasticities often suffer from misspecification bias as prices are rarely exogenous. Although instrumental variables can account for such endogeneity, it remains a challenge to find the appropriate instruments for prices. Indeed, previous studies have reported various levels of drilling elasticity, both in the short- and long-runs. Second, analyzing information spillover allows us to better understand the dynamics and interdependencies between energy prices and drilling/exploration activities. Such knowledge can help energy producers make more informed decisions on future oil and gas exploration activities and facilitate individual investors developing trading and investment strategies that better aligned with the market dynamics. For policymakers, such information can improve the forecast performance of energy market models, which are essential inputs to many macroeconomic prediction models.

3 Empirical Methods

To estimate the relationship between oil/gas rig counts and 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. Specifically, the VAR(p) is specified as:

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

where X_t is a column vector $[\textit{oil prices, oil rig count, gas prices, gas rig count}]'$. $\varepsilon_t \sim (0, \Omega)$ is a vector of independently and identically distributed disturbance with Ω being the covariance matrix, and p is the number of lags of the variables. We include oil and gas markets in the same model as energy firms may favor investing in one commodity over the other based on their relative profit margins. Additionally, since oil wells often simultaneously produce crude oil and associated gas, oil drilling activities may affect natural gas prices (and vice versa).

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 follows 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. 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.

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 connectedness index builds upon the forecast error variance decomposition (FEVD) of the VAR model, which decompose the H-step ahead forecast error of each variable into parts attributed to its shocks and shocks from other variables. The FEVD essentially indicates the amount of information each variable contributes to the variation in another variable from a forward-looking perspective. The forward-looking characteristic is appealing as it takes several months for energy firms to start a new well exploration. Following the DY framework, the decomposition matrix elements are subsequently aggregated to construct the directional connectedness between pairs of variables and the total-connectedness of the system.

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

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

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

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

$$C_{i \leftarrow j}(H) = \tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \times 100 \tag{3}$$

Equations (3) implies the row entry for any i^{th} variable is $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$, and the sum across all row variables equals N, i.e, $\sum_{j=1}^{N}\tilde{\theta}_{j}^{g}(H)=N$. Similarly, $C_{j\leftarrow i}(H)$ 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 $C_{ij}(H)=C_{i\leftarrow j}(H)-C_{j\leftarrow i}(H)$, can be used to determine which variable is the information transmitter, e.g., $C_{ij}(H)>0$, and which variable is the information receiver, e.g., $C_{ij}(H)<0$.

Additional connectedness indices can be constructed to evaluate the role of each variable in the overall information transmission system. Equations (4), (5), and (6) show the amount of information transmitted from all other variables to i, the information transmitted from i to all other variables, and the net information transmitted by i to the rest of the system, respectively,

$$C_{i\leftarrow\bullet}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4}$$

$$C_{\bullet\leftarrow i}(H)=\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{i=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\times 100 \tag{5}$$

$$C_{i}(H)=C_{i\leftarrow\bullet}(H)-C_{\bullet\leftarrow i}(H) \tag{6}$$

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

$$C(H)=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}=\frac{\sum_{i=1,i\neq j}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji}^{g}(H)}{N} \tag{7}$$

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 several lags, such that $C_{j\leftarrow i}(H)$ may be low at immediate horizons but increase as we move to more distant periods. Diebold and Yilmaz (2014) suggest taking precautions 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 re-balancing period.

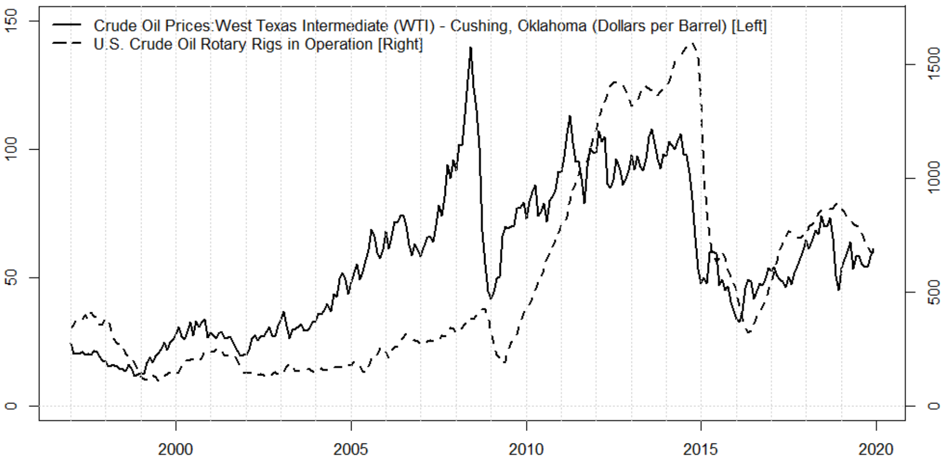
In our analysis, we focus on two forecast horizons, three months, and six months. Previous literature reports that a three- to six-month lag exists in the oil and gas industry. To drill a well, producers first have to secure funding and purchase the mining rights, and subsequently issue a request for quotation from drillers. Once drillers are awarded the contracts, the drillers' crew install the rig and start the extraction of reserves. Therefore the effect of oil or gas price changes may show up in drilling activities with several months lag . The chosen lags are consistent with Khalifa et al. (2017), who showed that the impact of oil prices on rig counts might show up with one-quarter lag.

Additionally, since one of our hypotheses is that the information contained in the rig count and energy prices may have evolved over time, we construct time-varying connectedness indices based on a rolling-window framework. The approach allows us to capture evolution in spillover patterns that may have occurred due to changes in the underlying economic conditions and business cycles, improvement in drilling and exploration technologies, shifts in energy policies and regulations, and development in financial market environments.

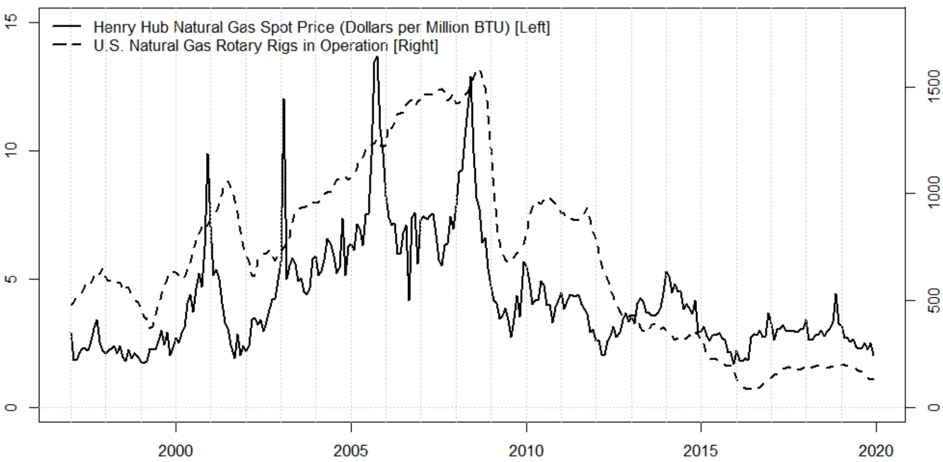
4 Data

Crude oil and natural gas rotary rigs in operation from the EIA database are used as a proxy for investment activities in the oil and gas industry. Crude oil and natural gas prices refer to the spot prices of West Texas Intermediate (WTI; in dollars per barrel) and Henry Hub (in dollars per million BTU), respectively. Some previous studies suggest that energy firms use futures prices to plan out exploration and development activities. We therefore also consider prices of futures contracts to expire in the next 12 months for crude oil and natural gas traded on the New York Mercantile Exchange (NYMEX). However, using spot and futures prices produced similar estimation results due to the high correlation between the two price sequences. We hence focus our discussions on spot prices.[4] The sample period consists of monthly data from January 1997 to December 2019.

Figure 1: Oil and Gas Prices, and Rig Counts, January 1997-December 2019



(a) Crude oil



(b) Natural gas

Figure 1 plots the prices (left axis) and rig counts (right axis) for crude oil and natural gas. In panel (a), the evolution of oil rigs overall resembles the behavior of oil prices, particularly after 2009. While oil prices sharply increased between 2000 and 2008, peaking in July 2008, oil rigs increased modestly during this period. After the dramatic decline

[4]The results using futures prices are available from the authors upon request.

during the 2008-2009 financial crisis, oil prices gradually bounced back and fluctuated between $85 to $135 per barrel in 2011-2014. During this period, oil rigs sharply increased and peaked in the second half of 2014. Since the end of 2014, oil prices started falling due to a weakening global demand. However, OPEC decided not to cut supply as a strategy to squeeze higher-cost competitors, including US shale producers, out of the market. The prices of oil subsequently plummeted, fluctuating between $30 to $75 per barrel in 2015-2019.

Panel (b) of Figure 1 shows the evolution of natural gas prices and gas rigs in operation during the sample period. Again, we observe a close correspondence between prices and rig counts. Natural gas prices were somewhat volatile before 2009. Since 2009, gas price volatility has significantly subdued. Interestingly, unlike oil rigs, the number of gas rigs dramatically decreased since 2009. In recent years, both gas prices and rig counts have stabilized at relatively low levels. Compared to oil, prices and rigs in operation for natural gas remain closely linked toward the end of the sample period.

Table 1: Summary Statistics of Data, January 1997-December 2019

Panel (a). Variables in Levels							
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). Variables in First Differences (in log)							
Variable	Summary statistics				Correlation matrix		
	Mean	Std dev	JB-test	ADF-test	ΔOil price	ΔOil rig count	ΔGas price
ΔOil price	0.60	0.09	9.63***	-7.26***	1		
ΔOil rig count	0.50	0.07	24.24***	-4.59***	-0.06	1	
ΔGas price	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: Summary statistics for real prices adjusted by CPI are reported in panel (a). ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively.

Table 1 reports the summary statistics and correlation coefficients for prices and rig counts. As shown in panel (a), the average number of rigs in operation is higher in the natural gas market than in oil. Meanwhile, oil rig count shows more variations than the gas rig count. Gas prices showed a slightly higher relative standard deviation (calculated as the standard deviation over mean) than oil prices (0.55 vs. 0.45).

The Augmented Dickey-Fuller (ADF) test shows that none of the four variables are stationary in levels. By contrast, their corresponding returns, calculated by the first differences in the logarithmic form, are all stationary. Therefore we consider the first-differenced data in the empirical analysis.[5] As can be seen in panel (b), natural gas returns are on average higher and more volatile than crude oil returns.

Furthermore, Table 1 shows that oil and natural gas prices positively correlate with their rig count, and the correlation coefficient appears to be higher in the gas market. Meanwhile, the two rig count variables are negatively correlated. However, changes in oil rigs are positively correlated with gas rig count changes, and the correlation is highly significant.

5 Empirical Results

This section reports the estimation results using crude oil and natural gas data from January 1997 to December 2019. All variables are specified in their logarithmic first differences. Based on the Akaike Information Criterion (AIC), five lags are included in the VAR model. In addition to seasonal dummy variables, we consider several exogenous variables to account for the macroeconomic effects. These variables include the TED Spread (the spread between 3-Month LIBOR and 3-Month Treasury Bill, used as an indicator of the perceived credit risk in the economy), the S&P 500 Index (an indicator of the overall economic performance), and the trade-weighted US dollar index against major currencies (an indicator for the impact of exchange rate on prices and investment activity). All data for the exogenous variables are obtained from the Federal Reserve Bank of St. Louis.

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

5.1 Full Sample Analysis

Based on the VAR model for the whole sample period, we first perform pairwise Granger causality tests, the results of which are presented in Table 2. we reject the null hypothesis that crude oil returns do not Granger cause changes in crude oil rig count. By contrast, lagged natural gas returns do not help predict changes in natural gas rig counts. Except 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 count in one market helps predict the rig count in the other market.

Table 2: Granger Causality Test Statistics, January 1997-December 2019

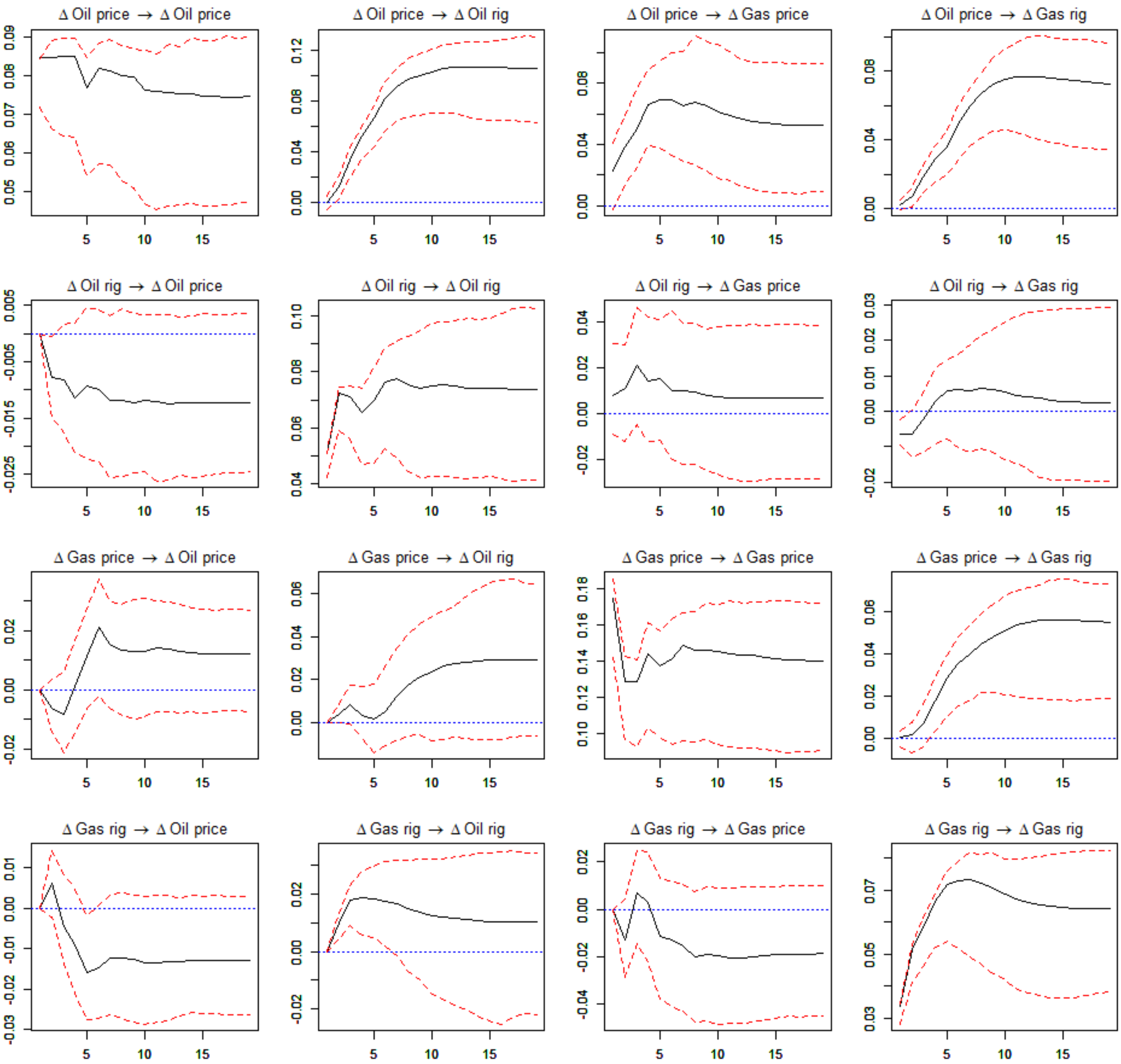
Null hypothesis	ΔOil price	ΔOil rig count	ΔGas price	ΔGas rig count
ΔOil price $\nrightarrow$ variables in top row	1.62	9.09***	2.38	2.44
ΔOil rig count $\nrightarrow$ variables in top row	1.20	58.00***	0.01	4.18**
ΔGas price $\nrightarrow$ variables in top row	0.78	1.26	13.74***	0.13
ΔGas rig count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

Notes: Granger causality tests are conducted based on the VAR model that uses monthly data from January 1997 to December 2019. Lags up to five months are included based on the AIC. Seasonal dummy variables and exogenous variables are included in the analysis. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

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 count respond positively to oil returns, suggesting that oil exploration and investment activities are sensitive to oil price changes. The positive response rapidly increases between one to ten months, after which it plateaus. A similar pattern is observed in the gas market, where gas rig count significantly increases after a positive shock to gas prices after month four. On the other hand, the responses of oil returns to oil rig count, as well as gas returns to gas rigs, are mostly negative and less significant.

Figure 2 further suggests that oil rig count positively respond to gas rig count, but this effect is only limited to the first six months after the shock occurred. Gas rig count reacts negatively in the first two months after a shock to oil rig count, and the response is

Figure 2: Cumulative Impulse Responses



Notes: Each cumulative response is calculated based on the VAR model that uses monthly data from January 1997 to December 2019. Lags up to five months are included based on the Akaike Information Criterion (AIC). Seasonal dummy variables and exogenous variables are included in the analysis. Each shock (impulse) is of one standard deviation in magnitude. Mean responses are plotted in the solid black line, and the 90% confidence intervals are plotted in red dotted lines.

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non-significant in the remaining months. Furthermore, gas rig count responds positively to oil returns, while oil rig count mostly does not respond to gas price changes. Overall, the Granger causality tests and impulse responses suggest that energy prices drive drilling activities, and oil and gas rig drilling are interlinked.

In Table 3, we report the connectedness indexes constructed based on the whole-

Table 3: Connectedness Indices Constructed Based on VAR Models

To \ From	ΔOil price	ΔOil rig count	ΔGas price	ΔGas rig count	Contrib. from others $C_{i\leftarrow\bullet}(H)$
			Panel (a) $H = 3$ months		
ΔOil price	94.14	0.96	1.68	2.23	*4.86*
ΔOil rig count	22.26	72.65	1.33	3.76	*27.35*
ΔGas price	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		
ΔOil price	91.54	1.02	4.59	2.84	*8.46*
ΔOil rig count	30.17	64.06	2.49	3.28	*35.94*
ΔGas price	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 column variable's contribution 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 received by i. $C_i(H)$ is the net-connectedness. $C(H)$ shows the total-connectedness index, which is the sum of all net-connectedness.

sample 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 of the four variables is 15.49% at the three-month forecast horizon, which increases to 22.53% at the six-month forecast horizon. Results show that most of the forecast error variance in crude oil and natural gas returns can be explained by their own variations (over 90% for both commodities). These percentages are slightly lower at the six-month horizon. However, the decreases are minimal, suggesting that oil and natural gas price changes are mostly driven by factors influencing their own market, independent of drilling activities and other factors.

For crude oil rig count, although its past values drive the majority of its variations, innovations from crude oil returns, natural gas returns, and natural gas rig count contribute 30.17%, 2.49%, and 3.28% to its forecast error variances at the six-month horizon, respectively. 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%) is almost twice as much as those from natural gas returns (e.g., 12.57%) at the six-month horizon. This suggests that crude oil price variations transfer more information to gas rig counts than natural gas price changes.

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 the overall information flow. On average, crude oil and natural gas returns are net information transmitters, while the two rig counts are net information receivers. The amount of information received and transmitted increase at the six-month horizon than that at a three-month horizon for all four variables. Further, crude oil returns are the most prominent information transmitter in the system, followed by natural gas returns and the two rig counts. This result is consistent with the dominant role crude oil prices play in the overall macro-economy.

The overall level of connectedness we found in this paper is smaller compare to other studies. For example, Scarcioffolo and Etienne (2019) find the connectedness in the US regional natural gas markets in the post-deregulation era to be between 50% and 70% at various daily horizons. Antonakakis (2012) finds a total spillover of 46.0% and 31.3% among exchange rates before and after introducing the Euro. Awartani and Maghyereh (2013) show an overall connectedness of 27.1% and 19.5% for the return and volatility spillover between oil prices and equities in the Middle-East. Kang et al. (2017) suggest that gold, silver, crude oil, wheat, and rice have a total-connectedness of 33.3% at the 10-week horizon.

A likely explanation for the disparity in the results is the use of different types of data. Previous studies either consider the prices for homogeneous goods (Scarcioffolo and Etienne, 2019; Awartani and Maghyereh, 2013) or various commodities (Kang et al., 2017; Diebold et al., 2017) that may present different levels of connectedness due to regulations, fundamental supply-and-demand factors, and other market-specific drivers. By contrast, our study is based on a mixture of variables with different properties — while oil and natural gas prices are determined by various supply-and-demand factors (rigs included), rig counts for oil and gas are directly driven by the expected profit of drilling that depends partially on prices and mining technology. The lower level of connectedness found in the present study should not come as a surprise since the linkage between prices and rigs is considerably less precise than between either homogeneous goods or different commodities.

5.2 Rolling Sample Analysis

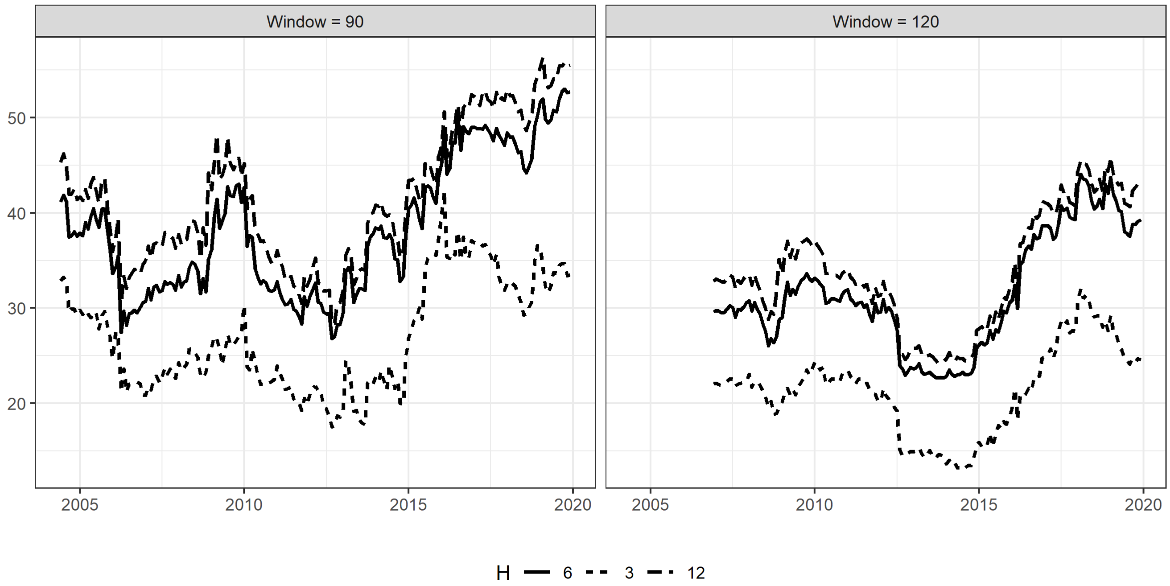
The oil and gas markets in the US have undergone tremendous volatility during the past few decades due to technological advances, market reforms, and other changes in the underlying market conditions. It is reasonable to assume that the shock transmitting mechanism between rigs and price changes may have evolved over our sample period as well. 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 (if any) occurred in the market but also allows for progressive, slowly-evolving developments due to technological advances, changes in consumer preferences, and business cycles (Scarcioffolo and Etienne, 2019).

Figure 3 plots the time-varying total-connectedness index when the window sizes are 90 and 120 months.[6] For robustness check, we present the total-connectedness with a forecast horizon of $H = 3$, 6, and 12 months. As shown in Figure 3, the evolution of the total-connectedness index shows similar patterns regardless of the window size. The total-connectedness for $H = 3$ mostly fluctuates between 15 and 40 percent for the two window sizes. 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.

Overall, the total connectedness has increased during the sample period. Note that the index had been mostly trending downward before mid-2012, suggesting an increasing

[6]Our data is monthly from January 1997 to December 2019 (276 observations). For $k = 4$ variables and $p = 5$ lags, the VAR model requires to estimate $p + kp^2 = 105$ parameters. Therefore, we analyze the rolling window of 90 and 120 months.

Figure 3: Total Connectedness Index Based on Rolling-Window Analysis



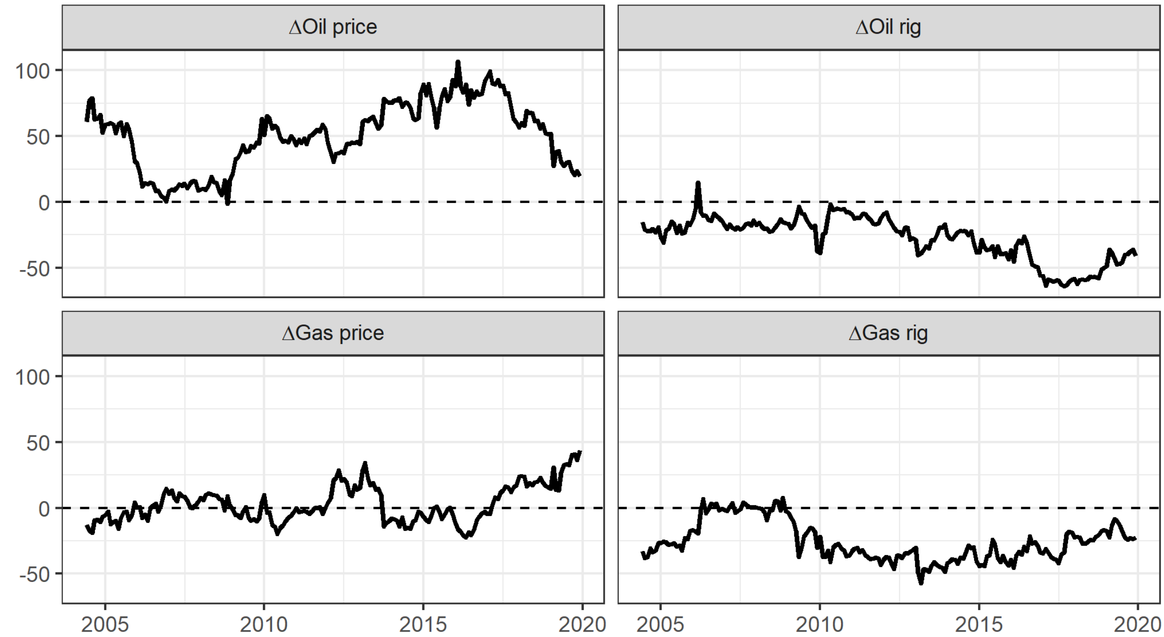
Notes: The connectedness index is constructed based on equation (7), using a rolling-window size of 90 months (left panel) and 120 months (right panel).

impact from other external factors that had weakened the linkage between rigs and prices in the US oil and gas sectors in the pre-shale era. This trend was reversed in 2012, when the returns and rig counts became more closely linked. Existing evidence mostly identifies 2004-2010 as the period when the unprecedented shale revolution took place in the US. Our results suggest that the rise of shale gas and tight oil production during this period has tightened the linkage between investment/drilling activities and prices. Scarcioffolo and Etienne (2019) note that the lowered per unit cost of production due to fracking has intensified competition between domestic oil and gas producers. The increasing market competitiveness has facilitated information transmission between oil/gas prices and rig counts, leading to a higher connectedness index within the system.

Figure 4 presents the rolling-window results of the net spillover for each variable considered in the study. To conserve space, we only report the results when the window size is 90 months, and the forecast horizon is six months.[7] Both oil and gas rig counts were a net receiver of information throughout most of the sample period. However, the net spillover indexes were increasing toward the end of the sample, suggesting the two rig

[7]Results for other window sizes and forecast horizons are available upon request.

Figure 4: Net Spillover Index Based on Rolling-Window Analysis



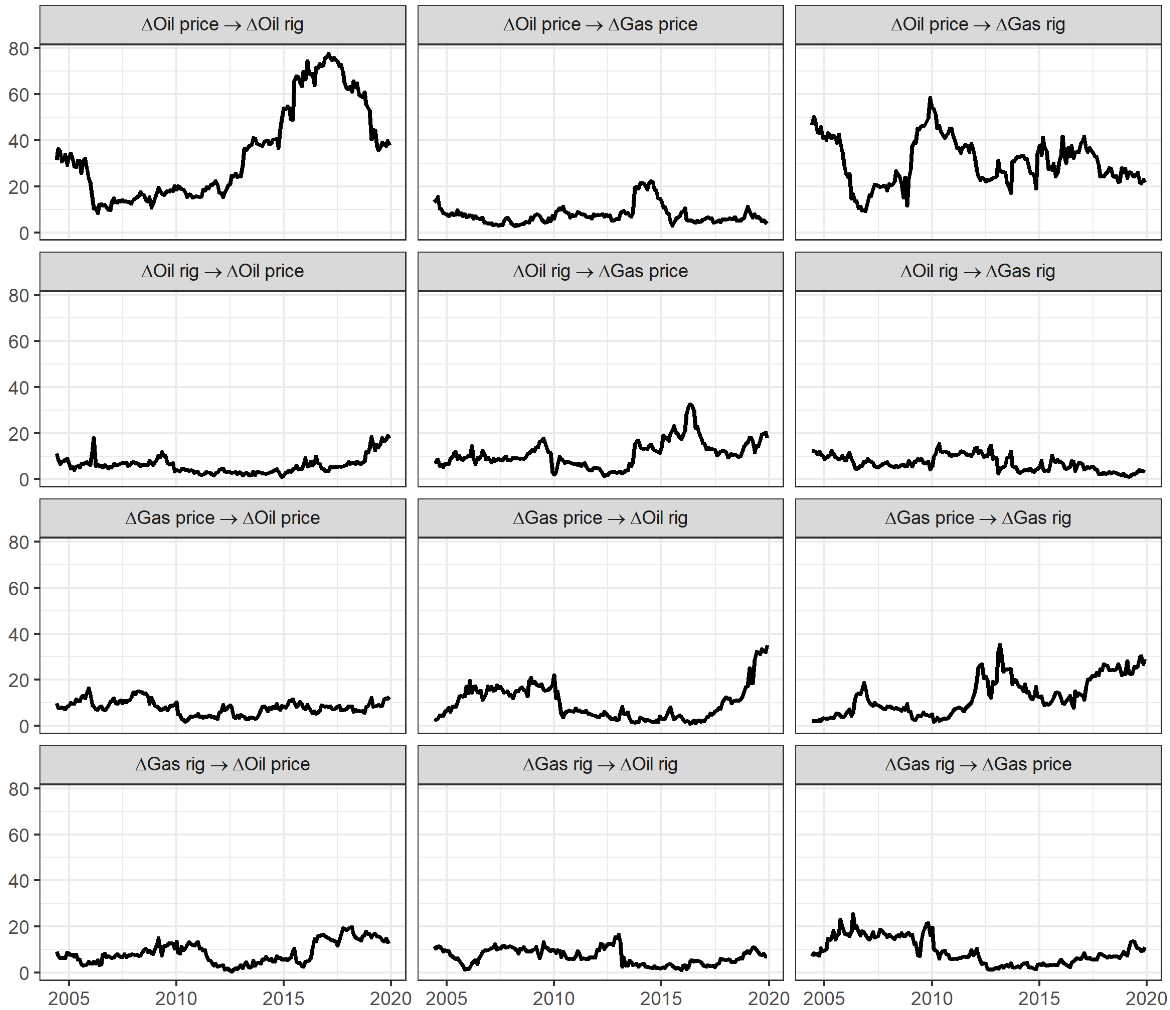
Notes: The net spillover index is constructed based on equation (6), using a rolling-window size of 90 months. A forecast horizon $H = 6$ months is considered.

counts were either transmitting more or/and receiving less information in the post-shale era.

Figure 4 further suggests that crude oil returns are net information spillover during the entire sample period, transmitting more information than receiving information from the other three variables. Consistent with the total connectedness index, the level of net information transmitted by oil shows a declining trend before 2012. Since 2012, the net-spillover index has gradually increased. However, since 2017 oil returns have been transmitting a much lower level of information within the system.

Compared to oil, net-spillover from gas returns is considerably less pronounced (lower left panel in Figure 4). Natural gas returns acted mostly as a net information receiver before 2007 and switched between an information transmitter and receiver from 2007 to 2012. In 2012-2014, natural gas returns became a significant information transmitter when shale gas production took off. Most notably, its role as an information transmitter has strengthened toward the end of the sample, during which the level of net information transmitted by oil had decreased. This period coincides with the rising importance of natural gas in the US energy mix, as natural gas overtook coal as the largest fuel source for power generation.

Figure 5: Pairwise Directional Connectedness Index Based on Rolling-Window Analysis



Notes: The pairwise directional spillover index is constructed based on equation (3), using a rolling-window of 90 months. A forecast horizon $H = 6$ months is considered.

Next, we show the sources of changes that determine the evolution of the net spillover index. Figure 5 plots the pairwise directional connectedness index, which shows how much information flows from one variable to another with a rolling window of 90 months for 6-month ahead forecast. As can be seen, oil returns spillover a significant amount of information to oil rigs, and the same holds for natural gas. However, the dynamics of the two spillover indexes are somewhat different. The level of information transmitted from oil returns to oil rig count significantly increased after 2012 (for samples including the initial shale period), peaking at around the end of 2016. Since late-2016, oil returns have been transmitting much less information to oil rigs. Although the directional connectedness index from gas returns to gas rigs also increased during the initial sample period, it had decreased between 2012 and 2017, which coincides with the early episode of the shale boom. Unlike oil, the level of information flown from gas returns to gas rigs had increased between 2017 and 2019.

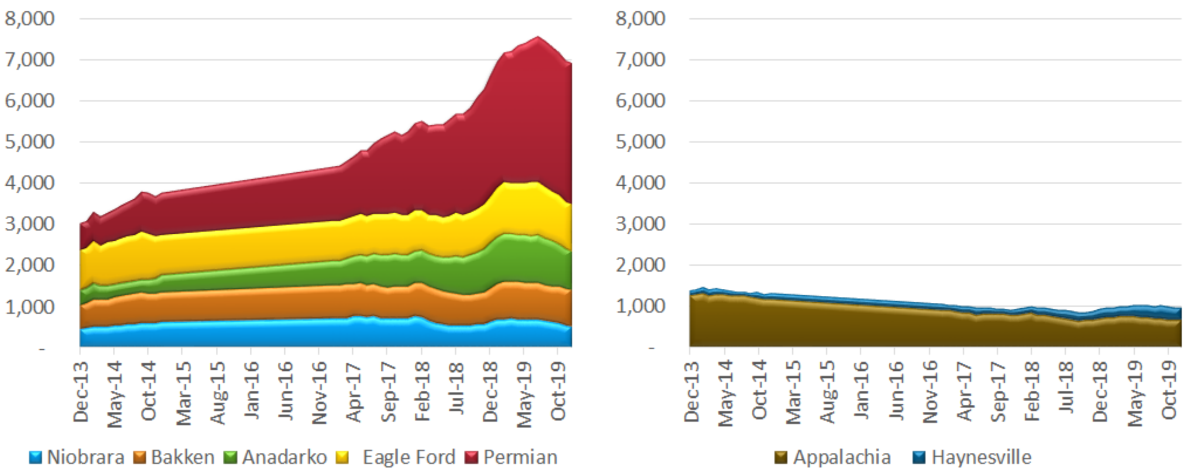
The observations from Figure 5 confirm our prior argument that the drilling activities in both the oil and gas industry, measured by rig counts, have overall become more responsive to price variations after the shale revolution. Although not directly comparable, these results corroborate the findings from Mason and Roberts (2018) who show that the gas drilling activities have become more price elastic in Wyoming after the shale boom, as well as Apergis et al. (2016) who find that oil drilling is highly sensitive to oil prices in some of the significant shale oil-producing regions in the US.

Compared to previous studies, our results provide additional insights on how output price changes affect drilling activities differently in the two energy markets. Oil drilling had indeed become more price responsive in the initial shale period, but the information transmitted from oil prices to rig count had declined when oil prices were fluctuating in a relatively stable range toward the end of the sample period. Several reasons may help explain the seemingly decoupling between oil price changes and drilling activity since late 2016 (for observations mostly occurred after the initial shale boom period). Firstly, the productivity of rigs has been rapidly rising since 2014. Brown et al. (2019) show that before 2014, the amount of oil produced per rig in the first one year of operation ranged between 200 and 400 thousand barrels; by 2016, it had peaked at over one million barrels per rig. Meanwhile, the cost of drilling new wells has been in steady decline since 2012 due to improved well designs, higher drilling efficiency, and better tools. The higher productivity and lower cost of drilling has dramatically improved the economic attractiveness of drilling new wells despite the low oil prices. Indeed, Ansari and Kaufmann

(2019) show that increased new rig productivity explains much of the recovery of oil rigs since 2016.

The lower level of information transmitted from oil to active oil rigs in recent years may also be partially driven by the rising number of drilled but uncompleted wells ("DUCs"). Indeed, data from the EIA (Figure 6) suggests that the DUCs in oil-dominant regions have been trending upwards since 2014, with the most significant increases came from the Permian Basin in recent years. Kleinberg et al. (2018) outline several reasons why DUCs occur, including the long-term nature of some rig renting contracts and the specification of land leasing contracts that require a certain level of drilling activity to take place in a given time-frame. Furthermore, energy firms may delay oil production from drilled oil wells due to pipeline capacity constraints for hydrocarbons or the expectation that oil prices would rise in the future.

Figure 6: Drilled but Uncompleted Wells in Oil- and Gas-Dominant Regions, 2013-2019



(a) Oil-dominant regions (b) Gas-dominant regions

Source: US Energy Information Administration, Drilling Productivity Report

Unlike oil, we find that the information transmitted from gas price changes to the number of active gas rigs has increased toward the end of the sample. This result is consistent with the finding from Ansari and Kaufmann (2019) that improvement in rig productivity and price changes account for much of the gas rig variations after 2016. In contrast, oil rig changes since 2016 were primarily driven by improvements in new rig productivity. Furthermore, as can be seen in Figure 6, the number of DUCs in the regions with significant shale gas production, including Appalachian and Haynesville, has decreased significantly since 2016. These regions have also added significant new pipeline capacity since 2014, improving their ability to transport natural gas to demand centers throughput the US. The higher integration between demand and production regions likely strengthened the linkage between prices and drilling activities.

Figure 5 suggests that the information transmitted from oil rigs to oil prices, as well as from gas rigs to gas prices, have consistently fluctuated around a relatively low level during the sample period. This finding is consistent with the impulse response function documented in Figure 2 where the response of oil and gas returns to a shock to their respective rig count is overall non-significant. One possible reason for the low impact of rig counts on oil and gas prices is that despite the rise in the number of active rigs drilling for oil and gas, the dramatic surge in unconventional energy production is primarily attributed to the productivity gains. Indeed, Ansari and Kaufmann (2019) simulate real oil prices assuming constant price volatility, finding that the changes in energy firms' revenue due to improvement in new rig productivity can explain much of the decline in oil prices since the shale revolution. Notably, their simulation analysis shows that the simulated oil prices align slightly less closely with observed prices after 2016, a possible indication of a more significant impact of oil rigs. This is consistent with Figure 5 where the the directional index from oil rigs to oil prices slightly increased after 2016.

Furthermore, estimation results in Figure 5 suggest that there exists a modest level of information transmission from oil rigs to gas prices, as well as from gas prices to oil rigs, both of which increased after 2016. The rise in information transmission is expected since much of the oil wells also produce natural gas (i.e., associated gas). Gas price changes would encourage/discourage drilling activities in the oil sector, while oil drilling activities also exert a non-negligible impact on gas prices. However, there exists little information spillover between the two rig count numbers.

6 Conclusions and Policy Implications

The rise of unconventional oil and gas production since the mid-2000s has revolutionized the US's energy sector. This paper investigates the interplay between oil/gas prices and drilling activities and how this relationship has evolved in light of the shale revolution. Using connectedness indexes constructed based on vector autoregression models, we find that the linkage between exploration and drilling activities, measured by active rotary rigs in operation, and oil and gas prices in the US has overall strengthened. The largest contributor to the rise of the total connectedness index appears to be the increased information transmitted from oil price changes to the number of active rigs drilling oil and gas. An increased level of information transmission is also observed from oil rigs to oil prices, from gas prices to gas rigs, from oil rigs to gas prices, and from gas prices to oil rigs.

We find that oil prices played a dominant role in information transmission between drilling activities and energy prices before 2017. Since the mid-2010s, however, natural gas price variations have become an increasingly important channel through which external shocks affect the energy sector in the US. This result is perhaps not unexpected given the increasing importance of natural gas in the US energy mix, which many consider the "bridge fuel" toward a clean-energy future. Energy firms should place a greater emphasis on the factors driving natural gas prices when weighing the investment options on drilling/exploration activities. Meanwhile, in designing policies to promote sustainable economic importance, it is essential to emphasise the role of natural gas price changes, perhaps by increasing the weights of gas prices in the macroeconomic forecasting models.

We further show that drilling activities in both the oil and gas markets have become more responsive to price variations since the shale revolution, as suggested by the greater amount of information transmitted from prices to rig counts. This result is consistent with the notion that unconventional oil and gas producers are more price-sensitive than conventional producers due to lower production uncertainty, shorter investment horizons, and faster production rate. However, the information transmitted from oil prices to rig count had declined when oil prices were fluctuating in a relatively stable range toward the end of the sample period. In contrast, the information transmitted from gas price changes to the number of active gas rigs has increased during the same time frame. The main reasons behind the decline of oil rig price sensitivity include the rise of rig productivity, stabilization of drilling cost, and the growing number of drilled but uncompleted wells. In light of the evolution of the directional spillover index from prices to drilling activities, a time-varying approach is needed to estimate the impact of energy price changes on oil/gas firms' investment behavior.

Although many consider oil and gas prices to have decoupled since the shale boom (e.g., Zhang and Ji, 2018), our results show that from a system-wide perspective, the linkage between drilling activities and oil/gas prices has strengthened. There is an increasing level of information transmission from oil rigs to gas prices and gas prices to oil rigs. The dual production nature of many of the oil wells and the resource competition channel between oil and gas investment suggest that the shocks to one sector may be transmitted to the other sector through drilling activities. Accounting for the linkage between the oil and gas sectors remains an important task for policymakers who wish to design policies for energy firms and other market participants.

Understanding the linkage between drilling activities and energy prices is a challenging task given a large number of supply-and-demand shocks involved in each market and the constantly time-varying nature of some variables, which extend beyond what our model and analysis could capture. Our paper provides evidence on the directional information channels in these two markets, shedding light on prudent drilling and investment decisions at varying market conditions, especially with the new technology development and the resulting rapid rise of unconventional oil and gas production. Future studies may wish to consider how other exogenous shocks, particularly those from the demand side, affect the relationship between drilling activities and energy prices.

References

Ansari, E. and Kaufmann, R. K. (2019). The effect of oil and gas price and price volatility on rig activity in tight formations and OPEC strategy. *Nature Energy*, 4(4):321–328.

Antonakakis, N. (2012). Exchange return co-movements and volatility spillovers before and after the introduction of euro. *Journal of International Financial Markets, Institutions and Money*, 22(5):1091–1109.

Apergis, N., Ewing, B. T., and Payne, J. E. (2016). A time series analysis of oil production, rig count and crude oil price: Evidence from six US oil producing regions. *Energy*, 97:339–349.

Awartani, B. and Maghyereh, A. I. (2013). Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council countries. *Energy Economics*, 36:28–42.

Baumeister, C. and Kilian, L. (2015). A general approach to recovering market expectations from futures prices with an application to crude oil. Working paper, Department of Economics, University of Notre Dame.

Baumeister, C. and Kilian, L. (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *Journal of Economic Perspectives*, 30(1):139–60.

Black, G. and LaFrance, J. T. (1998). Is Hotelling's rule relevant to domestic oil production? *Journal of Environmental Economics and Management*, 36(2):149–169.

Brigida, M. (2018). State dependence in the natural gas price and rig count relationship. *New York Economic Review*, 49:63–76.

Brown, J., Rodziewicz, D., and Colton, T. (2019). Drilling productivity in the United States: What lies beneath. *kcFED Economic Bulletin*, pages 1–5.

Diebold, F. X., Liu, L., and Yilmaz, K. (2017). Commodity connectedness. Working Paper 23685, National Bureau of Economic Research.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yilmaz, K. (2011). Equity market spillovers in the americas. *Financial Stability, Monetary Policy, and Central Banking*, 15:199–214.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Diebold, F. X. and Yilmaz, K. (2015). Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014. *Journal of Financial Econometrics*, 14(1):81–127.

EIA (2016). Trends in US oil and natural gas upstream costs. https://www.eia.gov/analysis/studies/drilling/.

Fattouh, B., Poudineh, R., and Sen, A. (2016). The dynamics of the revenue maximization–market share trade-off: Saudi Arabias oil policy in the 2014–15 price fall. *Oxford Review of Economic Policy*, 32(2):223–240.

Gülen, G., Browning, J., Ikonnikova, S., and Tinker, S. W. (2013). Well economics across ten tiers in low and high Btu (British thermal unit) areas, Barnett shale, Texas. *Energy*, 60:302–315.

Hausman, C. and Kellogg, R. (2015). Welfare and distributional implications of shale gas. Working paper, National Bureau of Economic Research.

Hunt, L. C. and Ninomiya, Y. (2003). Unravelling trends and seasonality : A structural time series analysis of transport oil demand in the UK and Japan. *Energy Journal*, 24(3):63–96.

Iliescu, N. et al. (2018). Long-run co-movements between oil prices and rig count in the presence of structural breaks. *Economics Bulletin*, 38(2):1171–1179.

Kang, S. H., McIver, R., and Yoon, S.-M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, 62:19–32.

Kellogg, R. (2011). Learning by Drilling: Inter-firm Learning and Relationship Persistence in the Texas Oil patch. *The Quarterly Journal of Economics*, 126(4):1961–2004.

Kellogg, R. (2014). The effect of uncertainty on investment: Evidence from Texas oil drilling. *American Economic Review*, 104(6):1698–1734.

Khalifa, A., Caporin, M., and Hammoudeh, S. (2017). The relationship between oil prices and rig counts: The importance of lags. *Energy Economics*, 63:213–226.

Kleinberg, R. L., Paltsev, S., Ebinger, C., Hobbs, D., and Boersma, T. (2018). Tight oil market dynamics: Benchmarks, breakeven points, and inelasticities. *Energy Economics*, 70:70–83.

Koop, G., Pesaran, M., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Lasky, M. (2016). The outlook for US production of shale oil. Technical report, Congressional Budget Office Working Paper 2016-01.

Mason, C. F. and Roberts, G. (2018). Price elasticity of supply and productivity: An analysis of natural gas wells in wyoming. *The Energy Journal*, 39(Special Issue 1).

Mohn, K. and Osmundsen, P. (2008). Exploration economics in a regulated petroleum province: The case of the Norwegian continental shelf. *Energy Economics*, 30(2):303–320.

Newell, R. G., Prest, B. C., and Vissing, A. B. (2019). Trophy hunting versus manufacturing energy: The price responsiveness of shale gas. *Journal of the Association of Environmental and Resource Economists*, 6(2):391–431.

Osmundsen, P., Roll, K. H., and Tveters, R. (2010). Exploration drilling productivity at the Norwegian shelf. *Journal of Petroleum Science and Engineering*, 73(1):122–128.

Osmundsen, P., Srenes, T., and Toft, A. (2008). Drilling contracts and incentives. *Energy Policy*, 36(8):3138–3144.

Pesaran, H. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17–29.

Ringlund, G. B., Rosendahl, K. E., and Skjerpen, T. (2008). Does oil rig activity react to oil price changes? an empirical investigation. *Energy Economics*, 30(2):371–396.

Scarcioffolo, A. R. and Etienne, X. L. (2019). How connected are the U.S. regional natural gas markets in the post-deregulation era? Evidence from time-varying connectedness analysis. *Journal of Commodity Markets*, 15:100076.

Trembath, A., Jenkins, J., Nordhaus, T., and Shellenberger, M. (2012). Where the shale gas revolution came from. `https://thebreakthrough.org/issues/energy/where-the-shale-gas-revolution-came-from`.

Wiggins, S. and Etienne, X. L. (2017). Turbulent times: Uncovering the origins of us natural gas price fluctuations since deregulation. *Energy Economics*, 64:196–205.

Zhang, D. and Ji, Q. (2018). Further evidence on the debate of oil-gas price decoupling: A long memory approach. *Energy Policy*, 113:68–75.