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Asymmetric Effects of Prices and Storage on Rig Counts: Evidence from the US Natural Gas and Crude Oil Markets

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Abstract: This study empirically investigates the asymmetric effects of spot (future) prices and storage on rig counts in the US natural gas and crude oil markets from January 1986 to May 2020. It adopts the Nonlinear Autoregressive Distributed Lag (NARDL) model and establishes a flexible and efficient framework that measures the effects of positive and negative shocks in each of these variables on rig counts while modeling possible asymmetries in both the short and long term. For the natural gas market, the results reveal significant long-term asymmetric effects of spot (future) gas prices and storage on gas rigs. The positive and statistically significant cumulative effect of changes in natural gas storage suggests that larger natural gas storage has caused changes in the use of natural gas drilling rigs. For the crude oil market, we find significant short-term asymmetric effects of spot (future) gas prices and oil stocks on oil rigs. Furthermore, in addition to the optimal price and level of storage, the cost, as proxied by the interest rate, is a crucial determinant in rig drilling decision-making in the energy sector.

Keywords: rig counts; natural gas market; crude oil market; storage; stocks; Nonlinear Autoregressive Distributed Lag (NARDL) model

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1. Introduction

During the last 20 years, and especially the last 10 years, the shale revolution has significantly changed the world energy market. Due to the application of new technologies in horizontal drilling and fracturing oil and gas production has reached new milestones. The resulting output increases have directly impacted price dynamics by providing unprecedented growth in recent years. With increasing demand caused by the economic growth of third-world countries and the financialization of commodities, prices of oil and natural gas have risen significantly. High oil and natural gas prices have led to renewed interest in investment in the energy sector. Due to the steady rise in demand and the resulting higher prices, investment in the energy sector has become profitable, leading to more exploration and production (E&P) activities in the fossil fuel industry, especially the oil and natural gas sectors.

Investment in natural resource exploration and drilling is irreversible, which has long been a critical issue for firms. The real option theory can be applied to the pricing of E&P projects. According to the theory, the value of drilling activities is determined by multiple factors, including the underlying value of the project, which is related to the price of natural resources, price uncertainties [1], and convenience yield [2], among others. Several authors have extended their efforts in this field. For instance, some authors studied development and exploration in the oil industry [3–6], while some have empirically investigated the associations between crude oil and gas prices and rig count [7–9].

The rig count is a key indicator of crude oil and natural gas development and exploration activity. Industry practitioners closely monitor rig counts (In fact, Baker Hughes collects and disseminates weekly US rig count information every Friday; these data are widely reported and discussed within the industry. Baker Hughes reports drilling rigs by location (land, inland waters, and offshore), type (oil or gas and directional, horizontal, or vertical), state, and major basin.). Figures 1 and 2 show the US rig count and natural gas spot price (Henry Hub price) on a monthly basis. The figures show that these two variables have followed a similar trajectory over the last 20 years. Around 2008–2009, both the rig count and gas price rose rapidly and reached very high levels, only to plummet at the onset of the most recent US recession in 2008.

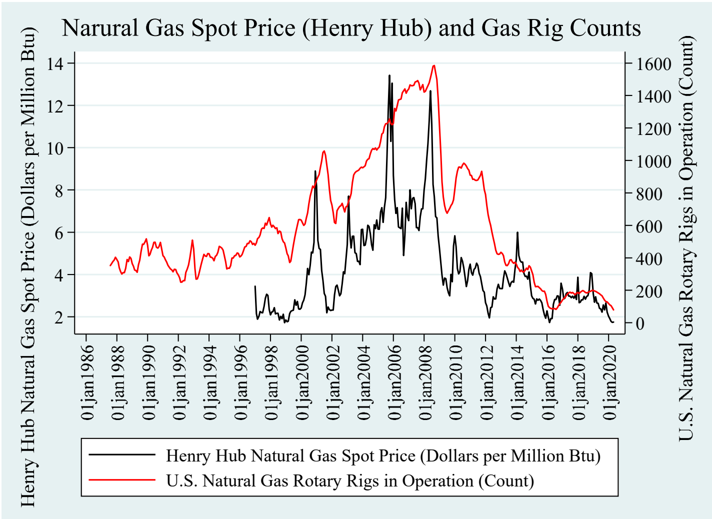

Figure 1. Time series of natural gas price and gas rig count. Data source: Baker Hughes and the US Department of Energy, Energy Information Administration (EIA).

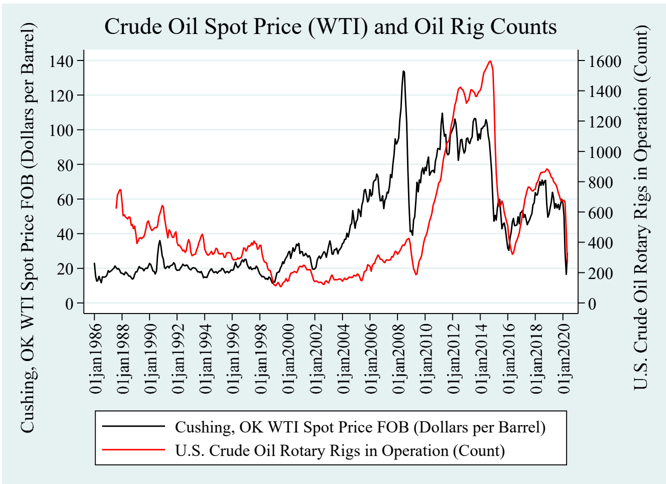

Figure 2. Time series of crude oil price and oil rig count. Data source: Baker Hughes and the US Department of Energy, Energy Information Administration (EIA).

Generally, one would expect the rig count and price to have a straightforward relationship; with more rigs being drilled, production will increase and prices will tend to decrease. However, whether this relationship holds empirically, what causes drilling to occur, and whether drilling results in higher production are all unclear. Hence, we propose two relevant hypotheses regarding their connections: (1) the price effect hypothesis, which suggests that higher or lower prices will lead to a higher or lower rig count, respectively; and (2) the rig count effect, which suggests that a higher or lower rig count will lead to lower or higher gas prices, respectively.

According to the price effect hypothesis, higher prices result in more investment due to an increase in the net present value of the project. The increase in investment results in more producing wells. Higher prices enable production companies to obtain sufficient revenue to acquire more debt to grow. Price increases are necessary to enable companies to invest more in exploration activities. Hence, when gas prices are high, producing companies can replenish depleted reserves with new reserves, allowing them to drill more wells. Furthermore, with high gas prices firms will be able to drill wells that would have been unprofitable to drill at lower price levels.

In the oil and natural gas industry, as companies develop unproven and undeveloped wells into proven, developed, and producing wells they typically drill larger wells first. As prices remain high, companies are able to drill in areas where initial large wells were drilled. This suggests that the rig count–price relationship is not linear, and depends on the level of the natural gas price. However, the rig count effect hypothesis follows the conventional notion of demand and supply, in which more drilling rigs lead to greater production, resulting in lower natural gas prices. According to this hypothesis, increases/decreases in rig count correlate with increases/decreases in natural gas production.

A preliminary analysis of these hypotheses can be obtained from scatter plots (see Figures 3 and 4). As the price effect hypothesis implies a positive relationship between the rig count and price and the rig count effect hypothesis implies a negative relationship between the rig count and price, a scatter plot of the two variables can help us to understand the possible connection. The price effect hypothesis appears to have greater potential to be supported by the data.

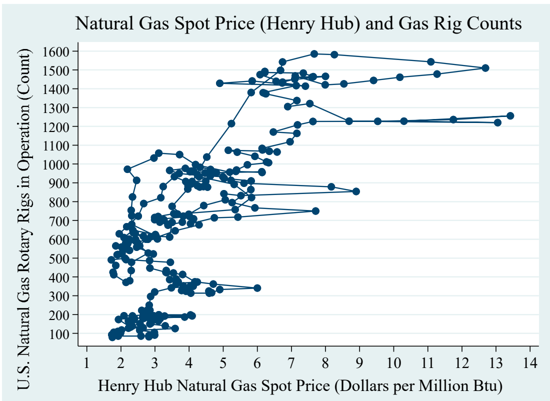

Figure 3. Relationship between natural gas price and gas rig count. Data source: Baker Hughes and the US Department of Energy, Energy Information Administration (EIA).

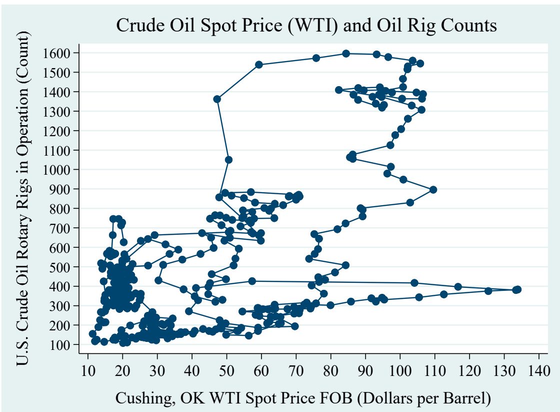

Figure 4. Relationship between crude oil price and oil rig count. Data source: Baker Hughes and the US Department of Energy, Energy Information Administration (EIA).

The above charts show a positive correlation between the rig count and price, suggesting that the price effect hypothesis is more likely to be supported by the data. Furthermore, real option theory suggests that price uncertainty discourages investment, and further implies that only sustained price increases can trigger an increase in rig count. This is supported by the above graph, which shows several episodes of price spikes. These spikes were caused by abnormally cold weather in the winters of 2000 and 2002 and by Gulf storms in the summers of 2005 and 2008. These price spikes were not accompanied by an increase in rig count, as these spikes did not represent a sustained price increase. This observation reinforces our assumption that there could be a nonlinear relationship between rig count and price. Thus, previous studies based on the assumption of a linear rig count–price nexus [8,10–12] are insufficient to substantiate this observed relationship, and it warrants further investigation.

In this study, we attempt to clearly determine the rig count–price relationship based on our observations as a way to complement existing studies. Previous studies have identified the existence of nonlinearity and extended research efforts toward disentangling the rig count–price relationship. Previous study empirically investigated the impact of changes in oil price on the rig count, finding that the rig count had a one-quarter lag influence on price changes [13]. They provided both linear and nonlinear evidence of the relationships; however, they failed to specifically identify the thresholds of different regimes, nor did they discuss the long-term relationships among the variables, which are of particular interest to academics and practitioners for long-term policy considerations. In a similar fashion, the relationship between the oil rig count and spot oil price and production was explored and discovered that investment activities as proxied by the oil rig count responded positively to changes in oil spot prices in the US using the NARDL framework [11]. Our work differs from theirs in several ways. First, as suggested by previous study, any drilling investment resulting in future output and future output prices can be secured in futures contracts [8]. This implies that future prices are more appropriate than spot prices when considered in the context of investment decision-making. For comparison, our study includes both spot and future prices. Second, we investigate both the oil market and the natural gas market, as both markets are intricately and closely linked. As the number of rigs is constant over time, the use of more rigs to explore for natural gas would reduce the availability of rigs to explore for oil, and vice versa. To illustrate this effect, we use the change in the number of crude oil rigs in our modeling setting. In this way our study provides a deeper understanding of the market interaction, which is more important in investment decisions as opposed to in a single market.

In this paper, we extend the extant literature by accounting for many important and relevant control variables associated with natural gas prices that may influence the energy sector, among which are storage impacts and weather factors. The reasons for including factors in our model settings are discussed in Section 2. The same section clarifies the importance of examining the short-term and long-term relationships in the rig count–price nexus. The remainder of the paper is organized as follows. Section 3 describes our data sources and provides a brief overview of the dataset; Section 4 then discusses the methodology applied to test Granger causality, co-integration, and the threshold models under the assumption of asymmetric price impacts. We provide measurements of the related factors and details on the procedure adopted to isolate the impact of unconventional gas production. Section 5 reports the empirical results of the models, and Section 6 concludes the paper.

2. Review of the Related Literature

2.1. Time Effect in the Rig Count–Price Nexus

The advancement of horizontal drilling and hydraulic fracturing technology is expected to significantly increase the productivity of oil wells. A long-term equilibrium relationship among the oil production differences in oil-producing areas over a period of time was found in previous study [14]. Furthermore, the number of oil rigs and crude oil prices have positive and statistically significant coefficients for total oil production. Although the rise in crude oil prices has resulted in a reduced number of rigs, those with horizontal drilling and hydraulic fracturing technology are found to be most sensitive to crude oil prices. In the short term, crude oil prices drive the total oil production and rig numbers in each region. In the long term, a feedback effect occurs between the total oil production and the number of rigs, rather than crude oil prices. Therefore, in evaluating oil companies and capital investment projects it is vital to determine regional differences in total oil production, the number of oil rigs, and crude oil prices in relation to oil-drilling activity. The long-term and short-term elasticity were estimated, respectively [15], while drilling rigs reacted more to changes in natural gas rigs than oil rigs and that they responded to actual oil prices rather than to actual natural gas prices. Research results indicate that while drilling rigs are highly flexible to changes in natural gas drilling rigs and actual oil prices in the short term, they are insensitive to changes in natural gas prices. According to the error correction model, changes in the use of drilling rigs are adjusted to eliminate the long-term imbalance between drilling rigs and commodity prices.

The rig count–price relationship may change over time. Recently, the relationship between oil prices and drilling rigs is proved and lagged rather than contemporaneous [10]. This means that changes in oil prices do not directly cause changes in the number of rigs. The number of non-shale drilling rigs is more resilient to the negative impact of oil. The negative correlation is lower considering the differences in the hysteresis of shale-drilling rigs. As the lag time under consideration increases, the asymmetry of the drilling platform's response to oil prices above the median becomes more pronounced. This can be translated into a different response to the rig count, which will have a greater impact during a bearish oil market. Considering the time required to activate the new rig, the insignificance of the positive oil shock coefficient can explain the need for a longer delay. Therefore, it might take longer for a positive oil shock to have an impact.

Previous studies examined how domestic oil drilling impacts the uncertainty of oil prices [16]. They measured domestic drilling activities by the number of rigs drilling for oil each week, while oil uncertainty was measured by the implied volatility of future oil options. It was found that the uncertainty of oil has a significantly negative impact on the number of rigs, with an increase of one standard deviation in uncertainty reducing the number of rigs by up to 4%. Moreover, the same study found that the number of domestic drilling rigs responded quickly to changes in oil prices within four weeks. The structural dynamics model used to estimate the demand for oil and the alternative measures based on the uncertainty of the time series econometric model were both found to be robust.

2.2. Storage

The idea that storage influences fuel prices is valid from a theoretical standpoint and empirically supported. The relationship between storage and commodity prices has been discussed since 1993, when Holbrook Working published the theory of storage. By highlighting the connection between the value of storage of a commodity and the volume of this commodity in storage, and how storage can influence the commodity's yield, previous studies have presented an elaboration of the storage theory [17–20]. They proposed that changing amounts of a commodity under storage could lead to price fluctuations. Likewise, analyst forecasts in the natural gas storage market are investigated and how analysts facilitate price discovery in futures markets was studied [21]. They discovered that the market appears to condition expectations regarding a weekly storage release based on analysts' forecasts, and places greater emphasis on analysts' long-term accuracy than on their recent accuracy.

Storage has been proven to be a fundamental driver in the energy market. Previous study examined how natural gas storage injections and withdrawals affected natural gas supply and demand conditions and studied the effect of gas storage injections or withdrawals on the residual volatility in future natural gas prices [22]. Moreover, some empirical evidence that supported the significant influence of storage on natural gas prices and their volatility was provided [23]. As the US natural gas market has evolved from a highly regulated market to a deregulated one [24], weather-affected natural gas prices have rendered it one of the most unstable markets. Over time, the causal flow from crude oil and cracking diffusion to natural gas has occurred simultaneously [25]. From the perspective of contemporaneous relations, this allows us to understand the divergence and convergence of oil and gas relations. Additionally, reserve changes and seasonality have a simultaneous and lagging causal relationship with natural gas, confirming that weather conditions and inventories determine natural gas prices. Finally, the impact of speculative activities on natural gas volatility is minimal, indicating that the financial role of the natural gas market remains limited. To date, financialization has not been the primary driver behind natural gas prices. Empirical analysis shows that there is a long-term equilibrium relationship between crude oil and natural gas price returns when taking other factors into consideration.

Inventory announcements have played a crucial role in stimulating the price dynamics of energy products. The effect of oil and gas inventory announcements on energy prices was examined and found that energy prices are more strongly influenced by unexpected changes in inventory than previously shown [26]. Moreover, some jumps in daily futures prices and intraday price fluctuations associated with inventory announcements of crude oil, heating oil, and natural gas were identified by using intraday data from January 1990 to January 2008 [27]. They found that the Energy Information Administration's inventory announcement dates tended to experience greater fluctuations and that the volatility and trading volume were higher on days with a jump in the inventory announcement than on days without a jump in the announcement.

2.3. Weather Impacts

Conversely, weather influences the pricing of many agricultural and energy commodities. It is found that El Niño–Southern Oscillation (ENSO) influenced crop production and was associated with low grain yields [28]. Several studies have examined the relationship between weather and commodity prices [29,30]. Their findings indicated that weather factors, especially temperature, significantly impacted commodity prices. It was found that both the energy and agriculture industries are considered weather-sensitive [31]. In addition, it was pointed out that the energy industry is especially vulnerable to weather risks when considering that the energy demand is highly dependent on weather conditions. For instance, while the demand for gasoline and jet fuel is highly seasonal, it is not sensitive to temperature [32]. However, electricity, natural gas, and heating oil consumption are all sensitive to the weather. Specificlly, the weather significantly impacts electricity demand and energy consumption and directly influences electricity prices [33]. Despite the importance of weather in determining the demand for natural gas, few studies have examined the direct effects of weather on the natural gas market [34].

3. Data Sources

The primary sample for the empirical analysis covers January 1986 to May 2020. Oil exploration data consist of the weekly number of onshore rotary rigs actively exploring or developing oil or natural gas in the US; this information is compiled by Baker Hughes. The weekly and monthly rig count data for countries are from Baker Hughes, and the weekly data are converted into monthly data by simple averaging. The Energy Information Administration (EIA) of the US Department of Energy provides monthly gas price data and unconventional natural gas data, including production, storage, and gas wells. The weather variables are taken from AccuWeather.com, a commercial source of weather information.

4. Methodology

Our empirical method is based on several observations and stylized facts regarding rig counts and the prices of crude oil and natural gas, respectively. Preliminary test results indicate that both variables are non-stationary. Therefore, we rely on non-stationary time-series methods to test our hypotheses.

Granger causality is the first method that we employ to test the association between spot (future) prices and rig count, establishing a simple linear causal relationship between the two variables. Then, based on the idea that higher prices lead to greater rig counts, we assume that the relationship between the rig count and spot (future) price depends on the value of the price. Due to low prices, only high-capacity production wells are drilled, as firms can cover their production costs. At higher prices, firms can expand into more drilling areas, leading to a lower production volume per well. Firms can do this because the higher prices cover the increased cost of drilling. When prices are low, firms may temporarily stop drilling. Consequently, firms will respond quickly to rising prices, and there will be more drilling activity [35]. When spot (future) prices increase and the drilling capacity is almost full (higher production wells having been developed), the higher prices are not able to induce drilling activity at the same pace. Accordingly, the drilling response to rising spot (future) prices differs: at lower prices, the drilling response is higher, while at higher prices the drilling response is lower.

4.1. Modeling Related Weather Factors

We use temperature variables to capture the impact of weather on gas prices, assuming that the temperature directly affects the demand for oil and natural gas. Thus, we define the temperature measures as cooling degree days (*CDD*) and heating degree days (*HDD*) [36]. A cooling degree day occurs when 65 °F is subtracted from the actual temperature and the result is greater than zero. A heating degree day occurs when the actual temperature is subtracted from 65 °F and the result is lower than zero. The definitions of *HDD* and *CDD* are as follows: $CDD_t = max(0,\ TD_t - 65F)$; $HDD_t = max(0,\ 65F - TD_t)$; $TD_t = (Tmax_t - Tmin_t)/2$ is the temperature for day t; $Tmax_t$ is the maximum temperature; and $Tmin_t$ is the minimum temperature for date t. The temperature shock *HDDs* and *CDDs* represent the respective monthly accumulation of daily *CDDs* and *HDDs* for a particular month.

4.2. Modeling the Storage Surprises of Natural Gas

To measure storage surprises, we assume that the storage level depends on the demand influenced by the temperature. Therefore, we consider the temperature as a key variable influencing the expected changes in natural gas storage. Thus, we determine the storage change in the following way [23]: $\Delta NGS_t = \alpha_0 + \alpha_1 \times TEMP_t + \varepsilon_t$, where ΔNGS_t is the expected change in storage released by the EIA for the month t and $TEMP_t$ is the weighted average temperature of natural gas consumption for month t. Therefore, the storage surprise (ε_t) is calculated as the difference between the actual storage change announced by the EIA and the expected storage change.

4.3. Isolating the Impact of Unconventional Energy Production

Unconventional natural gas (crude oil) production, represented by shale gas production, has grown exponentially, possibly leading to a distorted relationship between the rig count and gas (crude oil) prices. Lack of data prevents a full analysis of the effects of unconventional gas (crude oil). However, in this study we aim to determine the impact of shale gas on production and rig counts by controlling for the unconventional gas production/well variables. This is a reasonable approach, as unconventional gas production is not considered to be endogenously determined by gas prices. Instead, technological advancement in horizontal drilling has led to a rise in shale gas production. We rerun the test using the shale gas production/well as an exogenous or control variable to check the robustness of the test results [37].

4.4. Other Control Variables

We assume that the oil price influences the gas industry sector and that the oil rig count influences the gas production. It is possible that oil can enter the gas sector, as both oil and gas are competitive fuels and because oil is a member of the energy sector, which means that the demand for energy in general (economic and financial investment demand, linked to the financialization of the commodity market) can influence both. The oil rig count influences the gas market due to the technological linkage of oil wells producing associated gas. Thus, the oil rig count can significantly impact the gas industry variables. Hence, we use the lag of the oil rig count as an explanatory variable [8].

The rest of the control variables are included in order to improve the model's explanatory power and facilitate comparison. The log change in steel prices serves as a proxy for drilling costs, while the one-year T-bond rate serves as a control measure for the financial costs.

4.5. Empirical Specifications

4.5.1. Natural Gas Rigs

Benchmark model:

We apply an autoregressive distributed lag (ARDL) in terms of first differences, allowing us to control for certain factors potentially affecting rig drilling decisions [8]. To test the effect of spot prices on the rig counts for natural gas, we estimate the following Model (1) for our sample:

Model (1): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \; & \beta_0 + \sum_{i=0}^{m} \delta_i \Delta ln\left(Spot_{t-i}^{NG}\right) + \phi_1\left(\sum_{i=0}^{m} \hat{\delta}_i\right) + \sum_{i=0}^{m} \mu_i \Delta ln\left(Storage_{t-i}^{NG}\right) + \omega_1\left(\sum_{i=0}^{m} \hat{\mu}_i\right) \\ & + \beta_1 \Delta ln\left(Rig_t^{Oil}\right) + \beta_2 \Delta ln\left(Production_t^{NG}\right) \\ & + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{1}$$

where $\Delta ln\left(Rig_t^{NG}\right)$ represents the change in the natural logarithmic count of natural gas rigs in month t; $\sum_{i=0}^{m} \delta_i \Delta ln\left(Spot_{t-i}^{NG}\right)$ represents the change in the natural logarithm of spot prices in the previous month ($t - i$) for i = 0, 1, 2, 3 … m, testing for whether the driver of rig count changes influences changes in spot prices; and $\Delta ln\left(Storage_{t-i}^{NG}\right)$ indicates the change in the natural logarithm of natural gas storage in the previous month ($t - i$) for i = 0, 1, 2, 3 … m, as a measure of the influence of rig count changes on changes in gas storage. We account for the crowding out effect we consider the change in the number of crude oil rigs $\Delta ln\left(Rig_t^{Oil}\right)$ in the natural logarithm of the natural gas model [8]; $\Delta ln\left(Production_t^{NG}\right)$ measures changes in the natural logarithm of natural gas production, while HDD_t and CDD_t are the heating degree days (HDD) and cooling degree days (CDD), respectively. Additionally, $\Delta ln(PIPE_t)$ is the logarithm of changes in an index of steel pipe prices, implicating that drilling costs affect drilling decisions and a major proportion of the drilling costs. Following previous reseach [1,8], INT_t is included as the six-month treasury bond rate reflecting the costs due to fluctuating interest rates across business cycles. This additionally serves as a control for the estimated cost of launching energy projects under various economic circumstances; $\sum_{j=1}^{11}\left(\pi_j T_t^j\right)$ denotes dummy variables that take the value 1 when the month is j and not December and 0 otherwise, where j = 1, 2, 3,…, 11, representing January, February, etc., and November, respectively. This variable aims to gauge the seasonal effects of weather conditions on gas rig activity. Both ε_{t-1}^{NG} and ε_{t-2}^{NG} denote the permitted autocorrelation of residuals for the above model.

Moreover, we applied polynomial distributed lags (PDLs), which are finite-order distributed lag models with impulse-response functions constrained to stand on polynomials of known degrees [8]. Therefore, $\phi_1\left(\sum_{i=0}^{m} \hat{\delta}_i\right)$ in Model (1) denotes a quadratic impact structure of gas spot prices, where the index i represents the lag: $\hat{\delta}_i = f_0 + f_1 i + f_2 i^2$, where i = 1, 2, 3, and 4. We include four lags of spot price variables in the gas (oil) market regressions. We focus on the cumulative effects of spot price changes on natural gas drilling activity changes [8]. Therefore, we compute sums of $\left(\sum_{i=0}^{m} \hat{\delta}_i\right)$ for the spot price of natural gas. We specifically add $\omega_1\left(\sum_{i=0}^{m}\hat{\mu}_i\right)$ as a quadratic impact structure of the changes in gas storage, where the index i represents the lag [8]: $\hat{\mu}_i = g_0 + g_1 i + g_2 i^2$ as i = 1, 2, 3, and 4. When the values of δ_i (i = 1, 2, 3 . . . n) are positive and the sum is significantly different from zero, this is consistent with the conclusion that an increase in future gas prices tends to cause an increase in rig drilling activity for gas producers. If all values of δ_i (i = 1, 2, 3 . . . n) and the sum do not significantly differ from zero, we cannot reject the notion that there is no correlation between spot gas price changes and gas rig count changes.

Model (2): The future price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \;& \beta_0 + \sum_{i=0}^{m}\lambda_i \Delta ln\left(Future_{t-i}^{NG}\right) + \gamma_1\left(\sum_{i=0}^{m}\hat{\lambda}_i\right) + \sum_{i=0}^{m}\mu_i \Delta ln\left(Storage_{t-i}^{NG}\right) + \omega_1\left(\sum_{i=0}^{m}\hat{\mu}_i\right)\\ & + \beta_1 \Delta ln\left(Rig_t^{Oil}\right)\\ & + \beta_2 \Delta ln\left(Production_t^{NG}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right)\\ & + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{2}$$

Similarly, we model the effects of future gas prices on gas rig counts by including $\Delta ln\left(Future_{t-i}^{NG}\right)$, defined as the change in the natural logarithm of the future gas price. The remaining control variables are the same as in Model (1).

ARDL model

Model (3): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \;& \beta_0 + \sum_{i=1}^{n}\rho_i \Delta ln\left(Rig_{t-i}^{NG}\right) + \kappa_1\left(\sum_{i=1}^{n}\hat{\rho}_i\right) + \sum_{i=0}^{m}\delta_i \Delta ln\left(Spot_{t-i}^{NG}\right) + \phi_1\left(\sum_{i=0}^{m}\hat{\delta}_i\right)\\ & + \sum_{i=0}^{m}\mu_i \Delta ln\left(Storage_{t-i}^{NG}\right) + \omega_1\left(\sum_{i=0}^{m}\hat{\mu}_i\right)\\ & + \beta_1 \Delta ln\left(Rig_t^{Oil}\right) + \beta_2 \Delta ln\left(Production_t^{NG}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT_t\\ & + \sum_{j=1}^{11}\left(\pi_j T_t^j\right)\\ & + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{3}$$

In Model (3), we expand our baseline model to ARDL by considering the lagged gas rig counts; $\Delta ln\left(Rig_{t-i}^{NG}\right)$ denotes changes in the natural logarithm of the natural gas rig count in the previous month $(t-i)$ for i = 0, 1, 2, 3 . . . m, as a measure of the influence of rig count changes on changes in spot prices.

Model (4): The future price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \;& \beta_0 + \sum_{i=1}^{n}\rho_i \Delta ln\left(Rig_{t-i}^{NG}\right) + \kappa_1\left(\sum_{i=1}^{n}\hat{\rho}_i\right) + \sum_{i=0}^{m}\lambda_i \Delta ln\left(Futuret_{t-i}^{NG}\right) + \gamma_1\left(\sum_{i=0}^{m}\hat{\lambda}_i\right)\\ & + \sum_{i=0}^{m}\mu_i \Delta ln\left(Storage_{t-i}^{NG}\right) + \omega_1\left(\sum_{i=0}^{m}\hat{\mu}_i\right)\\ & + \beta_1 \Delta ln\left(Rig_t^{Oil}\right) + \beta_2 \Delta ln\left(Production_t^{NG}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT\\ & + \sum_{j=1}^{11}\left(\pi_j T_t^j\right)\\ & + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{4}$$

Based on Model (2), we extend our baseline model to ARDL by considering the lagged gas rig count $\Delta ln\left(Rig_{t-i}^{NG}\right)$ in the model.

NARDL model

Model (5): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \;& \beta_0 + \beta_1 ln\left(Rig_{t-1}^{NG}\right) + \theta_{NG}^{Positive} ln\left(Spot_t^{Positive}\right) + \theta_{Gas}^{Negative} ln\left(Spot_t^{Negative}\right) + \vartheta_{NG}^{Positive} ln\left(Storage_t^{Positive}\right) \\ & + \vartheta_{NG}^{Negative} ln\left(Storage_t^{Negative}\right) + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{NG}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) + \sum_{i=0}^{m}\left[\delta_i^{Positive} \Delta ln\left(Spot_{t-i}^{Positive}\right) + \delta_i^{Negative} \Delta ln\left(Spot_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\phi_{NG}^{Positive} \hat{\delta}_i^{Positive} + \phi_{NG}^{Negative} \hat{\delta}_i^{Negative}\right) + \sum_{i=0}^{m}\left[\mu_i^{Positive} \Delta ln\left(Storage_{t-i}^{Positive}\right) + \mu_i^{Negative} \Delta ln\left(Storage_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\omega_{NG}^{Positive} \hat{\mu}_i^{Positive} + \omega_{NG}^{Negative} \hat{\mu}_i^{Negative}\right) + \beta_2 \Delta ln\left(Rig_t^{Oil}\right) + \beta_3 \Delta ln\left(Production_t^{NG}\right) + \beta_4 HDD_t + \beta_5 CDD_t \\ & + \beta_6 \Delta ln(PIPE_t) + \beta_7 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{5}$$

where n and m are lag orders; $\theta_{NG}^{Positive}$ and $\theta_{Gas}^{Negative}$ denote partial positive and negative values of the natural logarithm of gas spot prices; and $\vartheta_{NG}^{Positive}$ and $\vartheta_{NG}^{Negative}$ represent partial positive and negative values of the natural logarithm of gas storage. Furthermore, $\delta_i^{Positive}$, $\delta_i^{Negative}$, $\mu_i^{Positive}$, and $\mu_i^{Negative}$ are the partial sums of positive and negative changes in each of the explanatory variables $\Delta ln\left(Spot_{t-i}^{Positive}\right)$, $\Delta ln\left(Spot_{t-i}^{Negative}\right)$, $\Delta ln\left(Storage_{t-i}^{Positive}\right)$, and $\Delta ln\left(Storage_{t-i}^{Negative}\right)$, respectively. Specifically, both $\sum_{i=1}^{m} \delta_i^{Positive}(\sum_{i=1}^{m} \mu_i^{Positive})$ and $\sum_{i=1}^{m} \delta_i^{Negative}(\sum_{i=1}^{m} \mu_i^{Negative})$ measure the short-term effects of changes in the natural logarithm of gas spot prices (gas storage) on gas rigs. In contrast to Model (3), Model (5) includes one lagged natural logarithm of gas rigs $ln\left(Rig_{t-1}^{NG}\right)$.

Model (6): The future price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{NG}\right) = \;& \beta_0 + \beta_1 ln\left(Rig_{t-1}^{NG}\right) + \theta_{NG}^{Positive} ln\left(Future_t^{Positive}\right) + \theta_{NG}^{Negative} ln\left(Future_t^{Negative}\right) \\ & + \vartheta_{NG}^{Positive} ln\left(Storage_t^{Positive}\right) \\ & + \vartheta_{NG}^{Negative} ln\left(Storage_t^{Negative}\right) + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{NG}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) \\ & + \sum_{i=0}^{m}\left[\lambda_i^{Positive} \Delta ln\left(Future_{t-i}^{Positive}\right) + \lambda_i^{Negative} \Delta ln\left(Future_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\gamma_{NG}^{Positive} \hat{\lambda}_i^{Positive} + \gamma_{NG}^{Negative} \hat{\lambda}_i^{Negative}\right) \\ & + \sum_{i=0}^{m}\left[\mu_i^{Positive} \Delta ln\left(Storage_{t-i}^{Positive}\right) + \mu_i^{Negative} \Delta ln\left(Storage_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\omega_{NG}^{Positive} \hat{\mu}_i^{Positive} + \omega_{NG}^{Negative} \hat{\mu}_i^{Negative}\right) + \beta_2 \Delta ln\left(Rig_t^{Oil}\right) + \beta_3 \Delta ln\left(Production_t^{NG}\right) \\ & + \beta_4 HDD_t + \beta_5 CDD_t \\ & + \beta_6 \Delta ln(PIPE_t) + \beta_7 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{NG} + \alpha_2 \varepsilon_{t-2}^{NG} + \psi_t\end{aligned} \tag{6}$$

Model (6) considers the asymmetric effects of (future) gas prices and gas storage on changes in gas rigs. Similar to the specification of Model (5), n and m are lag orders; $\theta_{NG}^{Positive}$ and $\theta_{Gas}^{Negative}$ denote partial positive and negative values of the natural logarithm of future gas prices; and $\vartheta_{NG}^{Positive}$ and $\vartheta_{NG}^{Negative}$ represent partial positive and negative values of the natural logarithm of gas storage, while $\lambda_i^{Positive}$, $\lambda_i^{Negative}$, $\mu_i^{Positive}$, and $\mu_i^{Negative}$ are the partial sums of positive and negative changes in $\Delta ln\left(Future_{t-i}^{Positive}\right)$, $\Delta ln\left(Future_{t-i}^{Negative}\right)$, $\Delta ln\left(Storage_{t-i}^{Positive}\right)$, and $\Delta ln\left(Storage_{t-i}^{Negative}\right)$, respectively. Specifically, both $\sum_{i=1}^{m} \lambda_i^{Positive}(\sum_{i=1}^{m} \mu_i^{Positive})$ and $\sum_{i=1}^{m} \lambda_i^{Negative}(\sum_{i=1}^{m} \mu_i^{Negative})$ measure the short-term effects of changes in the natural logarithm of future gas prices (gas storage) on changes in gas rigs.

4.5.2. Crude Oil Rigs

Benchmark model:

Model (7): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \sum_{i=0}^{m} \delta_i \Delta ln\left(Spot_{t-i}^{Oil}\right) + \phi_1\left(\sum_{i=0}^{m} \hat{\delta}_i\right) + \sum_{i=0}^{m} \mu_i \Delta ln\left(Stocks_{t-i}^{Oil}\right) + \omega_1\left(\sum_{i=0}^{m} \hat{\mu}_i\right) + \beta_1 \Delta ln\left(Rig_t^{NG}\right) \\ & + \beta_2 \Delta ln\left(Production_t^{Oil}\right) \\ & + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t\end{aligned} \quad (7)$$

Likewise, in Model (7) we examine the effects of oil spot prices and oil stocks on the changes in crude oil rigs. The dependent variable $\Delta ln\left(Rig_t^{Oil}\right)$ represents the changes in the natural logarithm of crude oil rigs, while $\Delta ln\left(Spot_{t-i}^{Oil}\right)$ and $\Delta ln\left(Stocks_{t-i}^{Oil}\right)$ indicate the changes in the natural logarithm of crude oil stocks in the previous month ($t-i$) for i = 0, 1, 2, 3 … m, to test whether the driver of rig count changes influences crude oil stocks. According to our natural gas model, we consider the change in the number of natural gas rigs $\Delta ln\left(Rig_t^{NG}\right)$ in the natural logarithm of natural gas to model the substitution effect. The other explanatory variables are the same as in Models (1) and (2).

Model (8): The future price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \sum_{i=0}^{m} \lambda_i \Delta ln\left(Futuret_{t-i}^{Oil}\right) + \gamma_1\left(\sum_{i=0}^{m} \hat{\lambda}_i\right) + \sum_{i=0}^{m} \mu_i \Delta ln\left(Stocks_{t-i}^{Oil}\right) + \omega_1\left(\sum_{i=0}^{m} \hat{\mu}_i\right) \\ & + \beta_1 \Delta ln\left(Rig_t^{NG}\right) \\ & + \beta_2 \Delta ln\left(Production_t^{Oil}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) \\ & + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t\end{aligned} \quad (8)$$

Similar to Model (7), Model (8) examines the effects of future oil prices and oil stocks on crude oil rig counts; $\Delta ln\left(Future_{t-i}^{Oil}\right)$ is the change in the natural logarithm of (future) crude oil prices in the previous month ($t-i$) for i = 0, 1, 2, 3 … m.

ARDL model

Model (9): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{Oil}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) + \sum_{i=0}^{m} \delta_i \Delta ln\left(Spot_{t-i}^{Oil}\right) + \phi_1\left(\sum_{i=0}^{m} \hat{\delta}_i\right) \\ & + \sum_{i=0}^{m} \mu_i \Delta ln\left(Stock_{t-i}^{Oil}\right) + \omega_1\left(\sum_{i=0}^{m} \hat{\mu}_i\right) \\ & + \beta_1 \Delta ln\left(Rig_t^{NG}\right) + \beta_2 \Delta ln\left(Production_t^{Oil}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) \\ & + \beta_6 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t\end{aligned} \quad (9)$$

We expand Model (7) to ARDL by considering the lagged oil rig counts in the above model; $\Delta ln\left(Rig_{t-i}^{Oil}\right)$ and $\Delta ln\left(Spot_{t-i}^{Oil}\right)$ represent the changes in the natural logarithm of oil rigs and oil spot prices in the previous month ($t-i$) for i = 0, 1, 2, 3 … m, examining whether changes in both oil rig counts and oil spot prices occur.

Model (10): The future price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{Oil}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) + \sum_{i=0}^{m} \lambda_i \Delta ln\left(Future_{t-i}^{Oil}\right) + \gamma_1\left(\sum_{i=0}^{m} \hat{\lambda}_i\right) \\ & + \sum_{i=0}^{m} \mu_i \Delta ln\left(Stock_{t-i}^{Oil}\right) + \omega_1\left(\sum_{i=0}^{m} \hat{\mu}_i\right) \\ & + \beta_1 \Delta ln\left(Rig_t^{NG}\right) + \beta_2 \Delta ln\left(Production_t^{Oil}\right) + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 \Delta ln(PIPE_t) + \beta_6 INT \\ & + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) \\ & + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t \end{aligned} \quad (10)$$

We expand Model (8) to ARDL by incorporating the lagged oil rig counts in the above model; $\Delta ln\left(Rig_{t-i}^{Oil}\right)$ and $\Delta ln\left(Future_{t-i}^{Oil}\right)$ are the changes in the natural logarithm of oil rigs and (future) oil prices in the previous month ($t-i$) for i = 0, 1, 2, 3 ... m, allowing us to explore whether the driver of changes in oil rig counts influences lagged oil rigs and lagged future oil prices.

NARDL model

Model (11): The spot price effect

$$\begin{aligned}\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \beta_1 ln\left(Rig_{t-1}^{Oil}\right) + \theta_{Oil}^{Positive} ln\left(Spot_t^{Positive}\right) + \theta_{Oil}^{Negative} ln\left(Spot_t^{Negative}\right) \\ & + \vartheta_{Oil}^{Positive} ln\left(Stock_t^{Positive}\right) + \vartheta_{Oil}^{Negative} ln\left(Stock_t^{Negative}\right) \\ & + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{Oil}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) \\ & + \sum_{i=0}^{m}\left[\delta_i^{Positive} \Delta ln\left(Spot_{t-i}^{Positive}\right) + \delta_i^{Negative} \Delta ln\left(Spot_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\phi_{Oil}^{Positive} \hat{\delta}_i^{Positive} + \phi_{Oil}^{Negative} \hat{\delta}_i^{Negative}\right) \\ & + \sum_{i=0}^{m}\left[\mu_i^{Positive} \Delta ln\left(Stock_{t-i}^{Positive}\right) + \mu_i^{Negative} \Delta ln\left(Stock_{t-i}^{Negative}\right)\right] \\ & + \sum_{i=0}^{m}\left(\omega_{Oil}^{Positive} \hat{\mu}_i^{Positive} + \omega_{Oil}^{Negative} \hat{\mu}_i^{Negative}\right) + \beta_2 \Delta ln\left(Rig_t^{NG}\right) + \beta_3 \Delta ln\left(Production_t^{Oil}\right) \\ & + \beta_4 HDD_t + \beta_5 CDD_t \\ & + \beta_6 \Delta ln(PIPE_t) + \beta_7 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t \end{aligned} \quad (11)$$

Similar to the NARDL setting of natural gas, Model (11) aims to model the asymmetric effect of crude oil (spot) prices and stocks on oil rigs. Here, n and m are lag orders; $\theta_{NG}^{Positive}$ and $\theta_{Gas}^{Negative}$ represent the partial positive and negative values of the natural logarithm of oil spot prices; and $\vartheta_{NG}^{Positive}$ and $\vartheta_{NG}^{Negative}$ represent the partial positive and negative values of the natural logarithm of crude oil stocks. Furthermore, $\delta_i^{Positive}$, $\delta_i^{Negative}$, $\mu_i^{Positive}$, and $\mu_i^{Negative}$ are the partial sums of positive and negative changes in each of the explanatory variables $\Delta ln\left(Spot_{t-i}^{Positive}\right)$, $\Delta ln\left(Spot_{t-i}^{Negative}\right)$, $\Delta ln\left(Stock_{t-i}^{Positive}\right)$, and $\Delta ln\left(Stock_{t-i}^{Negative}\right)$, respectively. Specifically, both $\sum_{i=1}^{m} \delta_i^{Positive}(\sum_{i=1}^{m} \mu_i^{Positive})$ and $\sum_{i=1}^{m} \delta_i^{Negative}(\sum_{i=1}^{m} \mu_i^{Negative})$ measure the short-term effects of changes in the natural logarithm of oil spot prices (oil stocks) on oil rigs. In contrast to Model (3), Model (5) considers one lagged natural logarithm of gas rigs $ln\left(Rig_{t-1}^{NG}\right)$.

Model (12): The future price effect

$$\begin{aligned}
\Delta ln\left(Rig_t^{Oil}\right) = \; & \beta_0 + \beta_1 \ln\left(Rig_{t-1}^{Oil}\right) + \theta_{NG}^{Positive} ln\left(Future_t^{Positive}\right) + \theta_{Oil}^{Negative} ln\left(Future_t^{Negative}\right) + \vartheta_{Oil}^{Positive} ln\left(Stocks_t^{Positive}\right) \\
& + \vartheta_{Oil}^{Negative} ln\left(Stocks_t^{Negative}\right) + \sum_{i=1}^{n} \rho_i \Delta ln\left(Rig_{t-i}^{Oil}\right) + \kappa_1\left(\sum_{i=1}^{n} \hat{\rho}_i\right) \\
& + \sum_{i=0}^{m}\left[\lambda_i^{Positive} \Delta ln\left(Future_{t-i}^{Positive}\right) + \lambda_i^{Negative} \Delta ln\left(Future_{t-i}^{Negative}\right)\right] \\
& + \sum_{i=0}^{m}\left(\gamma_{Oil}^{Positive} \hat{\lambda}_i^{Positive} + \gamma_{Oil}^{Negative} \hat{\lambda}_i^{Negative}\right) \\
& + \sum_{i=0}^{m}\left[\mu_i^{Positive} \Delta ln\left(Stocks_{t-i}^{Positive}\right) + \mu_i^{Negative} \Delta ln\left(Stocks_{t-i}^{Negative}\right)\right] \\
& + \sum_{i=0}^{m}\left(\omega_{Oil}^{Positive} \hat{\mu}_i^{Positive} + \omega_{Oil}^{Negative} \hat{\mu}_i^{Negative}\right) + \beta_2 \Delta ln\left(Rig_t^{NG}\right) + \beta_3 \Delta ln\left(Production_t^{Oil}\right) + \beta_4 HDD_t \\
& + \beta_5 CDD_t \\
& + \beta_6 \Delta ln(PIPE_t) + \beta_7 INT_t + \sum_{j=1}^{11}\left(\pi_j T_t^j\right) + \alpha_1 \varepsilon_{t-1}^{Oil} + \alpha_2 \varepsilon_{t-2}^{Oil} + \psi_t
\end{aligned} \quad (12)$$

Model (12) is similar to Model (11) as it incorporates the positive and negative effects of (future) oil prices on the change in oil rig counts. Specifically, both $\sum_{i=1}^{m} \lambda_i^{Positive}$($\sum_{i=1}^{m} \mu_i^{Positive}$) and $\sum_{i=1}^{m} \lambda_i^{Negative}$($\sum_{i=1}^{m} \mu_i^{Negative}$) measure the short-term effect of changes in the natural logarithm of future oil prices (oil stocks) on the number of oil-drilling activities. The remaining control variables are the same as in Model (8). To mitigate serial correlation in our estimations, we use heteroscedasticity and autocorrelation consistent (HAC) standard errors, allowing for a maximum of five lags of serial correlatiom [38].

5. Empirical Results

We examine the relative total influence of future price changes against spot price changes, applying four-month lags to both variables. We report the overall effects of spot price changes on the rig count $\sum_{i=1}^{m} \hat{\delta}_i$, and the total influence of future price changes on rig count changes separately on the rig count $\sum_{i=1}^{m} \hat{\lambda}_i$ while simultaneously controlling for the overall effects of storage (stocks) on the rig count $\sum_{i=1}^{m} \hat{\mu}_i$.

5.1. Natural Gas Market

Panel A of Table 1 reports the empirical results of the baseline model for the natural gas market. The estimated results of Model (1) indicate that the cumulative effect of spot price changes ($\sum_{i=1}^{m} \hat{\delta}_i$) is 0.203 ($t$ = 3.840), which is positive and statistically significant. Therefore, higher gas spot prices economically promote the number of gas rigs. Furthermore, the cumulative effect of gas storage changes ($\sum_{i=1}^{m} \hat{\lambda}_i$) is 0.039 ($t$ = 1.810), which is positive and statistically significant. It confirms that larger gas storage significantly increases gas rig usage. Regarding the control variables, we find the coefficient of change in the oil rig to be 0.098 (t = 2.595). There is a positive and statistically significant relationship between the change in gas rigs and the change in oil rigs. We confirm the positive and significant association between the changes in steel pipe prices and the changes in gas rigs, which is in line with the previous findings [8]. Further, the relationship between the one-year treasury bond interest rate and the change in gas rigs is positive and statistically significant. Finally, error autocorrelation controlled with two lags (ε_{t-1}^{NG} and ε_{t-2}^{NG}) is reported to be positive and statistically significant as 0.539 (t = 6.092) and 0.213 (t = 3.190), respectively. Unfortunately, there is no significant evidence for the estimated coefficients of gas production, CDD, and HDD. Additionally, the results estimated according to Model (2) indicate that the cumulative effect of future gas price changes ($\sum_{i=1}^{m} \hat{\lambda}_i$) is 0.247 ($t$ = 3.880), which is positive and statistically significant. The results for both gas spot and future prices are significantly different from zero, with the impact of future price changes on decision making being greater than that of spot price changes. The cumulative effect of gas storage changes ($\sum_{i=1}^{m} \hat{\mu}_i$) is 0.035 ($t$ = 1.860), which is positive and statistically significant. The results for other control variables are similar to the findings of Model (2).

Table 1. Natural gas rig activity and storage.

Panel A: OLS Using Newey–West Heteroscedasticity—and Autocorrelation—Consistent Standard Errors				
Variable	**Dependent Variable =$\Delta ln\left(Rig_t^{Gas}\right)$, i.e., Changes in the Natural Logarithm of Number of Natural Gas Drilling Rigs**			
	Model (1)		**Model (2)**	
	Coefficient	**(*t*-Statistic)**	**Coefficient**	**(*t*-Statistic)**
Constant	−0.025	(−0.478)	0.027	(0.622)
$\Delta ln\left(Spot_t^{Gas}\right)$	0.006	(0.437)		
$\Delta ln\left(Spot_{t-1}^{Gas}\right)$	0.028	(1.369)		
$\Delta ln\left(Spot_{t-2}^{Gas}\right)$	0.053 **	(2.547)		
$\Delta ln\left(Spot_{t-3}^{Gas}\right)$	0.048 *	(1.728)		
$\Delta ln\left(Spot_{t-4}^{Gas}\right)$	0.067 ***	(3.249)		
$\sum_{i=0}^{m}\hat{\delta}_i$	0.203 ***	(3.840)		
$\Delta ln\left(Future_t^{Gas}\right)$			−0.000	(−0.020)
$\Delta ln\left(Future_{t-1}^{Gas}\right)$			0.038	(1.554)
$\Delta ln\left(Future_{t-2}^{Gas}\right)$			0.075 **	(2.367)
$\Delta ln\left(Future_{t-3}^{Gas}\right)$			0.053	(1.459)
$\Delta ln\left(Future_{t-4}^{Gas}\right)$			0.081 ***	(2.777)
$\sum_{i=0}^{m}\hat{\lambda}_i$			0.247 ***	(3.880)
$\Delta ln\left(Storage_t^{Gas}\right)$	−0.004	(−0.501)	0.005	(0.853)
$\Delta ln\left(Storage_{t-1}^{Gas}\right)$	0.010	(1.470)	0.007	(1.097)
$\Delta ln\left(Storage_{t-2}^{Gas}\right)$	0.015*	(1.937)	0.013 **	(2.016)
$\Delta ln\left(Storage_{t-3}^{Gas}\right)$	0.008	(1.002)	0.005	(0.755)
$\Delta ln\left(Storage_{t-4}^{Gas}\right)$	0.010	(1.134)	0.005	(0.682)
$\sum_{i=0}^{m}\hat{\mu}_i$	0.039 *	(1.810)	0.035 *	(1.860)
$\Delta ln\left(Rig_t^{Oil}\right)$	0.098 ***	(2.595)	0.101 **	(2.537)
$\Delta ln\left(Production_t^{Gas}\right)$	−0.006	(−0.135)	−0.042	(−0.972)
$ln(CDD_t)$	−0.000	(−0.055)	−0.007	(−1.159)
$ln(HDD_t)$	0.002	(0.410)	−0.003	(−0.584)
$\Delta ln(Pipe\ Prices_t)$	0.241 **	(2.324)	0.210 *	(1.899)
$(Treasury\ Bond\ Rate)_t^{6-month}$	0.003 ***	(2.763)	0.003 **	(2.485)
ε_{t-1}^{Gas}	0.539 ***	(6.092)	0.503 ***	(5.897)
ε_{t-2}^{Gas}	0.213 ***	(3.190)	0.235 ***	(3.998)
Monthly Fixed Effects	Yes		Yes	
Observations	276		313	
F-statistic	14.35 ***		12.97 ***	
Panel B: Autoregressive Distributed Lag (ARDL)				
Variable	**Dependent Variable =$\Delta ln\left(Rig_t^{Gas}\right)$, i.e., Changes in the Natural Logarithm of Number of Natural Gas Drilling Rigs**			
	Model (3)		**Model (4)**	
	Coefficient	**(*t*-Statistic)**	**Coefficient**	**(*t*-Statistic)**
Constant	−0.027	(−0.599)	0.034	(0.815)
$\Delta ln(Rig)_{t-1}^{Gas}$	0.627	(1.644)	0.376	(1.037)
$\Delta ln(Rig)_{t-2}^{Gas}$	−0.633	(−1.435)	−0.180	(−0.445)
$\Delta ln(Rig)_{t-3}^{Gas}$	0.509 **	(1.987)	0.303	(1.256)
$\Delta ln(Rig)_{t-4}^{Gas}$	−0.121 *	(−1.791)	−0.127 *	(−1.965)
$\sum_{i=0}^{n}\hat{\rho}_i$	0.382	(1.580)	0.372	(1.580)
$\Delta ln\left(Spot_t^{Gas}\right)$	0.011	(0.606)		
$\Delta ln\left(Spot_{t-1}^{Gas}\right)$	0.026	(1.406)		

Table 1. *Cont.*

$\Delta ln\left(Spot_{t-2}^{Gas}\right)$	0.061 ***	(3.098)		
$\Delta ln\left(Spot_{t-3}^{Gas}\right)$	0.049 **	(2.470)		
$\Delta ln\left(Spot_{t-4}^{Gas}\right)$	0.055 ***	(2.914)		
$\sum_{i=0}^{m} \hat{\delta}_i$	0.202 ***	(4.700)		
$\Delta ln\left(Future_t^{Gas}\right)$			0.007	(0.241)
$\Delta ln\left(Future_{t-1}^{Gas}\right)$			0.037	(1.273)
$\Delta ln\left(Future_{t-2}^{Gas}\right)$			0.078 ***	(2.615)
$\Delta ln\left(Future_{t-3}^{Gas}\right)$			0.048	(1.620)
$\Delta ln\left(Future_{t-4}^{Gas}\right)$			0.057 *	(1.928)
$\sum_{i=0}^{m} \hat{\lambda}_i$			0.227 ***	(4.040)
$\Delta ln\left(Storage_t^{Gas}\right)$	−0.001	(−0.118)	0.007	(0.985)
$\Delta ln\left(Storage_{t-1}^{Gas}\right)$	0.011	(1.436)	0.009	(1.289)
$\Delta ln\left(Storage_{t-2}^{Gas}\right)$	0.015 **	(2.111)	0.014 **	(2.160)
$\Delta ln\left(Storage_{t-3}^{Gas}\right)$	0.010	(1.305)	0.007	(1.035)
$\Delta ln\left(Storage_{t-4}^{Gas}\right)$	0.006	(0.680)	0.002	(0.236)
$\sum_{i=0}^{m} \hat{\mu}_i$	0.042 *	(1.780)	0.039 *	(1.830)
$\Delta ln\left(Rig_t^{Oil}\right)$	0.057 *	(1.769)	0.062 *	(1.943)
$\Delta ln\left(Production_t^{Gas}\right)$	−0.016	(−0.335)	−0.053	(−1.128)
$ln(CDD_t)$	0.000	(0.051)	−0.008	(−1.385)
$ln(HDD_t)$	0.003	(0.680)	−0.003	(−0.566)
$\Delta ln(Pipe\ Prices_t)$	0.147	(1.278)	0.123	(1.051)
$(Treasury\ Bond\ Rate)_t^{6-month}$	0.002	(1.513)	0.002 *	(1.705)
ε_{t-1}^{Gas}	−0.070	(−0.183)	0.142	(0.389)
ε_{t-2}^{Gas}	0.454	(1.189)	0.208	(0.574)
Monthly Fixed Effects	Yes		Yes	
Observations	276		313	
F-statistic	16.16 ***		15.85 ***	

Panel C: Nonlinear Autoregressive Distributed Lag (NARDL)

Dependent Variable =$\Delta ln\left(Rig_t^{Gas}\right)$, i.e., Changes in the Natural Logarithm of Number of Natural Gas Drilling Rigs

Variable	**Model (5)**		**Variable**	**Model (6)**	
	Coefficient	**(*t*-Statistic)**		**Coefficient**	**(*t*-Statistic)**
Constant	1.478 ***	(3.844)	Constant	0.361 **	(2.028)
$ln\left(Rig_{t-1}^{Gas}\right)$	−0.056 ***	(−4.544)	$ln\left(Rig_{t-1}^{Gas}\right)$	−0.030 ***	(−3.504)
$ln\left(Spot_t^{Positive}\right)$	0.079 ***	(4.367)	$ln\left(Future_t^{Positive}\right)$	0.047 ***	(3.499)
$ln\left(Spot_t^{Negative}\right)$	0.002	(0.146)	$ln\left(Future_t^{Negative}\right)$	0.032 **	(2.314)
$ln\left(Storage_{t-1}^{Positive}\right)$	−0.021	(−1.225)	$ln\left(Storage_{t-1}^{Positive}\right)$	−0.018	(−1.203)
$ln\left(Storage_{t-1}^{Negative}\right)$	0.001	(0.086)	$ln\left(Storage_{t-1}^{Negative}\right)$	−0.014	(−0.955)
$\Delta ln\left(Rig_{t-1}^{Gas}\right)$	0.385	(0.999)	$\Delta ln\left(Rig_{t-1}^{Gas}\right)$	0.404	(1.113)
$\Delta ln\left(Rig_{t-2}^{Gas}\right)$	−0.681	(−1.567)	$\Delta ln\left(Rig_{t-2}^{Gas}\right)$	−0.239	(−0.604)
$\Delta ln\left(Rig_{t-3}^{Gas}\right)$	0.594 **	(2.310)	$\Delta ln\left(Rig_{t-3}^{Gas}\right)$	0.306	(1.274)
$\Delta ln\left(Rig_{t-4}^{Gas}\right)$	−0.095	(−1.398)	$\Delta ln\left(Rig_{t-4}^{Gas}\right)$	−0.103	(−1.603)
$\sum_{i=1}^{n} \hat{\rho}_i$	0.201	(0.820)	$\sum_{i=1}^{n} \hat{\rho}_i$	0.367	(1.560)
$\Delta ln(Spot)_t^{Positive}$	0.003	(0.104)	$\Delta ln\left(Future_t^{Positive}\right)$	−0.034	(−0.659)
$\Delta ln(Spot)_{t-1}^{Positive}$	−0.035	(−0.947)	$\Delta ln\left(Future_{t-1}^{Positive}\right)$	−0.001	(−0.024)
$\Delta ln(Spot)_{t-2}^{Positive}$	−0.004	(−0.096)	$\Delta ln\left(Future_{t-2}^{Positive}\right)$	−0.072	(−1.382)
$\Delta ln(Spot)_{t-3}^{Positive}$	0.031	(0.851)	$\Delta ln\left(Future_{t-3}^{Positive}\right)$	0.075	(1.444)
$\Delta ln(Spot)_{t-4}^{Positive}$	0.020	(0.561)	$\Delta ln\left(Future_{t-4}^{Positive}\right)$	0.037	(0.729)

Table 1. *Cont.*

$\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$	0.016	(0.160)	$\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$	0.005	(0.050)
$\Delta ln(Spot)_t^{Negative}$	0.018	(0.496)	$\Delta ln\left(Future_t^{Negative}\right)$	0.033	(0.613)
$\Delta ln(Spot)_{t-1}^{Negative}$	0.031	(0.873)	$\Delta ln\left(Future_{t-1}^{Negative}\right)$	0.008	(0.139)
$\Delta ln(Spot)_{t-2}^{Negative}$	0.084 **	(2.338)	$\Delta ln\left(Future_{t-2}^{Negative}\right)$	0.203 ***	(3.651)
$\Delta ln(Spot)_{t-3}^{Negative}$	0.015	(0.415)	$\Delta ln\left(Future_{t-3}^{Negative}\right)$	−0.029	(−0.506)
$\Delta ln(Spot)_{t-4}^{Negative}$	0.062 *	(1.855)	$\Delta ln\left(Future_{t-4}^{Negative}\right)$	0.049	(0.868)
$\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$	0.208 ***	(2.740)	$\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$	0.264 ***	(2.400)
$\Delta ln\ (Storage)_t^{Positive}$	−0.021	(−1.389)	$\Delta ln\left(Storage_t^{Positive}\right)$	−0.016	(−1.138)
$\Delta ln\ (Storage)_{t-1}^{Positive}$	0.018 *	(1.657)	$\Delta ln\left(Storage_{t-1}^{Positive}\right)$	0.014	(1.423)
$\Delta ln\ (Storage)_{t-2}^{Positive}$	0.015	(1.557)	$\Delta ln\left(Storage_{t-2}^{Positive}\right)$	0.016 *	(1.846)
$\Delta ln\ (Storage)_{t-3}^{Positive}$	0.007	(0.567)	$\Delta ln\left(Storage_{t-3}^{Positive}\right)$	0.005	(0.486)
$\Delta ln\ (Storage)_{t-4}^{Positive}$	0.019	(1.466)	$\Delta ln\left(Storage_{t-4}^{Positive}\right)$	0.021	(1.633)
$\sum_{i=0}^{m} \hat{\mu}_i^{Positive}$	0.038	(1.320)	$\sum_{i=0}^{m} \hat{\mu}_i^{Positive}$	0.040	(1.510)
$\Delta ln\ (Storage)_t^{Negative}$	0.005	(0.332)	$\Delta ln\left(Storage_t^{Negative}\right)$	0.009	(0.611)
$\Delta ln\ (Storage)_{t-1}^{Negative}$	0.005	(0.261)	$\Delta ln\left(Storage_{t-1}^{Negative}\right)$	0.007	(0.396)
$\Delta ln\ (Storage)_{t-2}^{Negative}$	0.027	(1.417)	$\Delta ln\left(Storage_{t-2}^{Negative}\right)$	0.032 *	(1.777)
$\Delta ln\ (Storage)_{t-3}^{Negative}$	0.021	(1.172)	$\Delta ln(\ Storage_{t-3}^{Negative})$	0.015	(0.903)
$\Delta ln\ (Storage)_{t-4}^{Negative}$	−0.007	(−0.429)	$\Delta ln\left(Storage_{t-4}^{Negative}\right)$	−0.007	(−0.431)
$\sum_{i=1}^{m} \hat{\mu}_i^{Negative}$	0.051	(0.790)	$\sum_{i=1}^{m} \hat{\mu}_i^{Negative}$	0.056	(0.940)
$\Delta ln\left(Rig_t^{Oil}\right)$	0.067 **	(2.027)	$\Delta ln\left(Rig_t^{Oil}\right)$	0.068 **	(2.065)
$\Delta ln\left(Production_t^{Gas}\right)$	−0.037	(−0.756)	$\Delta ln\left(Production_t^{Gas}\right)$	−0.084 *	(−1.717)
$ln(CDD_t)$	0.004	(0.472)	$ln(CDD_t)$	−0.001	(−0.120)
$ln(HDD_t)$	0.006	(0.952)	$ln(HDD_t)$	0.003	(0.469)
$\Delta ln(Pipe\ Prices_t)$	0.146	(1.269)	$\Delta ln(Pipe\ Prices_t)$	0.078	(0.650)
$(Treasury\ Bond\ Rate)_t^{6-month}$	0.002	(1.114)	$(Treasury\ Bond\ Rate)_t^{6-month}$	0.001	(0.305)
ε_{t-1}^{Gas}	0.129	(0.334)	ε_{t-1}^{Gas}	0.100	(0.274)
ε_{t-2}^{Gas}	0.645 *	(1.678)	ε_{t-2}^{Gas}	0.232	(0.638)
Monthly Fixed Effects	Yes		Monthly Fixed Effects	Yes	
Observations	276		Observations	313	
F-statistic	10.98 ***		*F*-statistic	10.84 ***	

Asymmetry Statistics:

Variable	Coefficient	*F*-statistic	*p*-value	Variable	Coefficient	*F*-statistic	*p*-value
	Long-term effect [+] (Positive Effects)				Long-term effect [+] (Positive Effects)		
$ln\left(Spot_t^{Gas}\right)$	1.416	167.300 ***	0.000	$ln\left(Future_t^{Gas}\right)$	1.584	49.490 ***	0.000
$ln\ (Storage)_t^{Gas}$	−0.369	1.602	0.207	$ln\ (Storage)_t^{Gas}$	−0.598	1.335	0.249
	Long-term effect [−] (Negative Effects)				Long-term effect [−] (Negative Effects)		
$ln\left(Spot_t^{Gas}\right)$	−0.033	0.021	0.884	$ln\left(Future_t^{Gas}\right)$	−1.076	6.678 **	0.010
Variable	Long-term effect [+] (Positive Effects)			Variable	Long-term effect [+] (Positive Effects)		
	Coefficient	*F*-statistic	*p*-value		Coefficient	*F*-statistic	*p*-value
$ln\ (Storage)_t^{Gas}$	−0.025	0.007	0.931	$ln\ (Storage)_t^{Gas}$	0.471	0.835	0.362
	Long-term asymmetry				Long-term asymmetry		
$ln\left(Spot_t^{Gas}\right)$		33.580 ***	0.000	$ln\left(Future_t^{Gas}\right)$		1.131	0.288
$ln\ (Storage)_t^{Gas}$		41.140 ***	0.000	$ln\ (Storage)_t^{Gas}$		2.079	0.150
	Short-term asymmetry				Short-term asymmetry		
$ln\left(Spot_t^{Gas}\right)$		1.908	0.169	$ln\left(Future_t^{Gas}\right)$		2.074	0.151
$ln\ (Storage)_t^{Gas}$		0.035	0.851	$ln\ (Storage)_t^{Gas}$		0.057	0.811

Note: *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the levels of 10%, 5%, and 1%, respectively.

Panel B of Table 1 presents the empirical results of the ARDL model for the natural gas market. The results of Model (3) show that the coefficient estimates for the cumulative effects of both gas spot price changes and gas storage changes are 0.202 (t = 4.700) and 0.042 (t = 1.780), respectively, which are positive and statistically significant. However, the cumulative effects of gas rig changes ($\sum_{i=0}^{n} \hat{\rho}_i$) are insignificant at 0.382 (t = 1.580). In addition to the variable of oil rig changes, most control variables appear insignificant when we include the cumulative effects of gas rig changes. The results of Model (4) indicate that both the cumulative effects of future gas price changes ($\sum_{i=0}^{m} \hat{\lambda}_i$) and gas storage changes ($\sum_{i=0}^{m} \hat{\mu}_i$) are significantly and positively correlated with changes in the gas rig count. However, the cumulative effects of gas rig changes ($\sum_{i=0}^{n} \hat{\rho}_i$) remain insignificant.

Panel C of Table 1 presents the results of the NARDL model. Model (5) indicates that gas spot prices and gas storage may have asymmetric long-term impacts on changes in gas rig counts. We find that its negative partial sum $ln\left(Spot_t^{Negative}\right)$ is significant, with the coefficient of $\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$ as 0.208 with t = 2.740, unlike the positive one $ln\left(Spot_t^{Positive}\right)$, with the coefficient of $\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$ as 0.016 with t = 0.160. This suggests that in the long term gas spot prices affect changes in gas rig counts asymmetrically. However, we find no significant evidence ($\Delta ln\left(Storage_{t-i}^{Positive}\right)$ and $\Delta ln\left(Storage_{t-i}^{Negative}\right)$) of asymmetric impacts of gas storage on gas rig counts. Based on these results, we find only a long-term positive and significant effect of the gas spot price on changes in gas rigs, confirming the significant long-term asymmetric effect of gas spot prices and storage on gas rigs, while the short-term asymmetric effect on gas rigs is insignificant.

The findings of Model (6) present the long-term asymmetric effects of future gas prices and gas storage on changes in gas rig counts. We report that its negative partial sum $\Delta ln\left(Future_t^{Negative}\right)$ is insignificant, with the coefficient of $\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$ as 0.264 with t = 2.400, unlike the positive but insignificant one $\Delta ln\left(Spot_t^{Positive}\right)$, with the coefficient of $\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$ as 0.005 with t = 0.050. This evidence indicates that in the long term gas spot prices affect changes in gas rig counts asymmetrically. However, we find no significant evidence ($\Delta ln\left(Storage_{t-i}^{Positive}\right)$ and $\Delta ln\left(Storage_{t-i}^{Negative}\right)$) of the asymmetric impact of gas storage on the gas rig count. Based on these results, we merely find that the long-term positive and negative effects of future gas prices on changes in gas rigs are statistically significant, confirming the significant long-term asymmetric effect of future gas prices on gas rigs, while the short-term asymmetric effect on gas rigs is insignificant.

5.2. Crude Oil Market

Panel A of Table 2 reports the empirical results of the baseline model for the crude oil market. The estimated results of Model (7) indicate that the cumulative effect of spot oil price changes ($\sum_{i=1}^{m} \hat{\delta}_i$) is 0.470 ($t$ = 5.720), which is positive and statistically significant. Therefore, higher oil spot prices economically promote the number of crude oil rigs. Furthermore, the cumulative effect for oil stock changes ($\sum_{i=0}^{m} \hat{\mu}_i$) is −0.941 ($t$ = −1.550), which is negative and statistically insignificant. In terms of control variables, we find the coefficient of change in gas rigs to be 0.122 (t = 2.184). There is a positive and statistically significant relationship between the change in gas rigs and the change in oil rigs. We find a negative but insignificant association between the changes in steel pipe prices and the changes in oil rigs. Further, the positive relationship between the one-year treasury bond interest rate and the change in oil rigs is identified as insignificant. Finally, error autocorrelation controlled with two lags (ε_{t-1}^{NG} and ε_{t-2}^{NG}) is reported to be positive and significant as 0.482 (t = 6.057) and 0.120 (t = 2.220), respectively. Additionally, the results estimated according to Model (8) indicate that the cumulative effect of future gas price changes ($\sum_{i=1}^{m} \hat{\lambda}_i$) is 0.479 ($t$ = 5.690), which is positive and statistically significant. Results for both gas spot prices (Model (7)) and future gas prices are significantly different from zero, with the impact of the future price changes on decision making being greater than that of the spot price changes. The cumulative effect of gas storage changes ($\sum_{i=1}^{m} \hat{\mu}_i$) is −0.968 ($t$ = −1.590), which is negative but insignificant. The results for other control variables are similar to the findings of Model (7).

Table 2. Crude oil rig activity and stocks.

Panel A: OLS Using Newey–West Heteroscedasticity—and Autocorrelation-Consistent Standard Errors

Variable	Dependent Variable $=\Delta ln(Rig_t^{Oil})$, i.e., Changes in the Natural Logarithm of Number of Crude Oil Drilling Rigs			
	Model (7)		Model (8)	
	Coefficient	(t-Statistic)	Coefficient	(t-Statistic)
Constant	0.020	(0.386)	0.027	(0.622)
$\Delta ln(Spot_t^{Oil})$	−0.005	(−0.143)		
$\Delta ln(Spot_{t-1}^{Oil})$	0.235 ***	(3.915)		
$\Delta ln(Spot_{t-2}^{Oil})$	0.086 *	(1.868)		
$\Delta ln(Spot_{t-3}^{Oil})$	0.069 *	(1.830)		
$\Delta ln(Spot_{t-4}^{Oil})$	0.084 **	(2.525)		
$\sum_{i=0}^{m} \hat{\delta}_i$	0.470 ***	(5.720)		
$\Delta ln\left(Future_t^{Oil}\right)$			0.002	(0.064)
$\Delta ln\left(Future_{t-1}^{Oil}\right)$			0.233 ***	(3.841)
$\Delta ln\left(Future_{t-2}^{Oil}\right)$			0.086 *	(1.845)
$\Delta ln\left(Future_{t-3}^{Oil}\right)$			0.070 *	(1.837)
$\Delta ln\left(Future_{t-4}^{Oil}\right)$			0.088 ***	(2.665)
$\sum_{i=0}^{m} \hat{\lambda}_i$			0.479 ***	(5.690)
$\Delta ln(Stocks_t^{Oil})$	−0.011	(−0.036)	−0.028	(−0.091)
$\Delta ln(Stocks_{t-1}^{Oil})$	−0.142	(−0.436)	−0.151	(−0.466)
$\Delta ln(Stocks_{t-2}^{Oil})$	−0.523	(−1.524)	−0.538	(−1.565)
$\Delta ln(Stocks_{t-3}^{Oil})$	−0.407	(−1.073)	−0.404	(−1.067)
$\Delta ln(Stocks_{t-4}^{Oil})$	0.142	(0.443)	0.154	(0.475)
$\sum_{i=0}^{m} \hat{\mu}_i$	−0.941	(−1.550)	−0.968	(−1.590)
$\Delta ln(Rig_t^{Gas})$	0.122 **	(2.184)	0.122 **	(2.166)
$\Delta ln(Production_t^{Oil})$	0.096	(1.160)	0.097	(1.161)
$ln(CDD_t)$	−0.001	(−0.159)	−0.001	(−0.140)
$ln(HDD_t)$	−0.003	(−0.458)	−0.002	(−0.428)
$\Delta ln(Pipe\ Prices_t)$	−0.012	(−0.077)	−0.013	(−0.087)
$(Treasury\ Bond\ Rate)_t^{6-month}$	−0.002	(−1.603)	−0.002	(−1.623)
ε_{t-1}^{Oil}	0.482 ***	(6.057)	0.482 ***	(6.047)
ε_{t-2}^{Oil}	0.120 **	(2.220)	0.119 **	(2.193)
Monthly Fixed Effects	Yes		Yes	
Observations	388		388	
F-statistic	14.32 ***		14.49 ***	

Panel B: Autoregressive Distributed Lag (ARDL)

Variable	Dependent Variable $=\Delta ln(Rig_t^{Oil})$, i.e., Changes in the Natural Logarithm of Number of Crude Oil Drilling Rigs			
	Model (9)		Model (10)	
	Coefficient	(t-Statistic)	Coefficient	(t-Statistic)
Constant	−0.002	(−0.034)	−0.003	(−0.063)
$\Delta ln(Rig)_{t-1}^{Oil}$	0.469 ***	(8.643)	0.469 ***	(8.637)
$\Delta ln(Rig)_{t-2}^{Oil}$	0.742	(0.922)	0.747	(0.926)
$\Delta ln(Rig)_{t-3}^{Oil}$	−0.318	(−1.046)	−0.330	(−1.083)
$\Delta ln(Rig)_{t-4}^{Oil}$	0.177	(1.416)	0.182	(1.453)
$\sum_{i=0}^{n} \hat{\rho}_i$	1.070 *	(1.910)	1.067 *	(1.900)
$\Delta ln(Spot_t^{Oil})$	−0.001	(−0.048)		
$\Delta ln(Spot_{t-1}^{Oil})$	0.242 ***	(6.750)		
$\Delta ln(Spot_{t-2}^{Oil})$	0.099 **	(2.562)		
$\Delta ln(Spot_{t-3}^{Oil})$	0.094 **	(2.437)		
$\Delta ln(Spot_{t-4}^{Oil})$	0.102 **	(2.578)		
$\sum_{i=0}^{m} \hat{\delta}_i$	0.537 ***	(7.120)		
$\Delta ln\left(Future_t^{Oil}\right)$			0.005	(0.172)
$\Delta ln\left(Future_{t-1}^{Oil}\right)$			0.239 ***	(6.635)
$\Delta ln\left(Future_{t-2}^{Oil}\right)$			0.100 **	(2.536)
$\Delta ln\left(Future_{t-3}^{Oil}\right)$			0.096 **	(2.444)
$\Delta ln\left(Future_{t-4}^{Oil}\right)$			0.106 ***	(2.648)
$\sum_{i=0}^{m} \hat{\lambda}_i$			0.546 ***	(7.180)
$\Delta ln(Stocks_t^{Oil})$	0.022	(0.072)	0.003	(0.011)
$\Delta ln(Stocks_{t-1}^{Oil})$	−0.157	(−0.530)	−0.170	(−0.571)
$\Delta ln(Stocks_{t-2}^{Oil})$	−0.370	(−1.232)	−0.388	(−1.291)
$\Delta ln(Stocks_{t-3}^{Oil})$	−0.257	(−0.847)	−0.255	(−0.841)
$\Delta ln(Stocks_{t-4}^{Oil})$	0.290	(0.943)	0.302	(0.982)
$\sum_{i=0}^{m} \hat{\mu}_i$	−0.473	(−0.810)	−0.508	(−0.870)
$\Delta ln(Rig_t^{Gas})$	0.101 *	(1.846)	0.101 *	(1.835)

Table 2. *Cont.*

$\Delta ln\left(Production_t^{Oil}\right)$	0.082	(1.462)	0.082	(1.464)
$ln(CDD_t)$	0.002	(0.429)	0.003	(0.451)
$ln(HDD_t)$	−0.000	(−0.085)	−0.000	(−0.049)
$\Delta ln(Pipe\ Prices_t)$	−0.100	(−0.604)	−0.101	(−0.609)
$(Treasury\ Bond\ Rate)_t^{6-month}$	−0.001	(−1.188)	−0.001	(−1.199)
ε_{t-1}^{Gas}	−0.964	(−1.191)	−0.970	(−1.197)
ε_{t-2}^{Gas}	−0.336	(−0.842)	−0.327	(−0.820)
Monthly Fixed Effects	Yes		Yes	
Observations	387		387	
F-statistic	17.68 ***		17.58 ***	

Panel C: Nonlinear Autoregressive Distributed Lag (NARDL)

Dependent Variable =$\Delta ln\left(Rig_t^{Oil}\right)$, i.e., Changes in the Natural Logarithm of Number of Crude Oil Drilling Rigs

Variable	Model (11)		Variables	Model (12)	
	Coefficient	**(*t*-Statistic)**		**Coefficient**	**(*t*-Statistic)**
Constant	0.085	(1.346)	Constant	0.074	(1.261)
$ln\left(Rig_{t-1}^{Oil}\right)$	−0.015 **	(−2.412)	$ln\left(Rig_{t-1}^{Oil}\right)$	−0.014 **	(−2.338)
$ln\left(Spot_t^{Positive}\right)$	0.036 ***	(2.991)	$ln\left(Future_t^{Positive}\right)$	0.033 ***	(2.908)
$ln\left(Spot_t^{Negative}\right)$	0.012	(0.659)	$ln\left(Future_t^{Negative}\right)$	0.015	(0.781)
$ln\left(Storage_{t-1}^{Positive}\right)$	0.008	(0.067)	$ln\left(Storage_{t-1}^{Positive}\right)$	0.027	(0.226)
$ln\left(Storage_{t-1}^{Negative}\right)$	0.203 **	(2.380)	$ln\left(Storage_{t-1}^{Negative}\right)$	0.189 **	(2.193)
$\Delta ln\left(Rig_{t-1}^{Oil}\right)$	0.406 ***	(7.471)	$\Delta ln\left(Rig_{t-1}^{Oil}\right)$	0.407 ***	(7.482)
$\Delta ln\left(Rig_{t-2}^{Oil}\right)$	−0.164	(−0.196)	$\Delta ln\left(Rig_{t-2}^{Oil}\right)$	−0.141	(−0.168)
$\Delta ln\left(Rig_{t-3}^{Oil}\right)$	−0.041	(−0.133)	$\Delta ln\left(Rig_{t-3}^{Oil}\right)$	−0.059	(−0.190)
$\Delta ln\left(Rig_{t-4}^{Oil}\right)$	0.111	(0.905)	$\Delta ln\left(Rig_{t-4}^{Oil}\right)$	0.117	(0.951)
$\sum_{i=1}^{n} \hat{\rho}_i$	0.313	(0.530)	$\sum_{i=1}^{n} \hat{\rho}_i$	(0.550)	(0.550)
$\Delta ln(Spot)_t^{Positive}$	−0.026	(−0.413)	$\Delta ln\left(Future_t^{Positive}\right)$	−0.016	(−0.256)
$\Delta ln(Spot)_{t-1}^{Positive}$	0.102	(1.440)	$\Delta ln\left(Future_{t-1}^{Positive}\right)$	0.092	(1.277)
$\Delta ln(Spot)_{t-2}^{Positive}$	−0.106	(−1.518)	$\Delta ln\left(Future_{t-2}^{Positive}\right)$	−0.097	(−1.370)
$\Delta ln(Spot)_{t-3}^{Positive}$	0.006	(0.093)	$\Delta ln\left(Future_{t-3}^{Positive}\right)$	0.011	(0.156)
$\Delta ln(Spot)_{t-4}^{Positive}$	0.046	(0.670)	$\Delta ln\left(Future_{t-4}^{Positive}\right)$	0.040	(0.570)
$\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$	0.023	(0.160)	$\sum_{i=0}^{m} \hat{\delta}_i^{Positive}$	0.029	(0.200)
$\Delta ln(Spot)_t^{Negative}$	0.010	(0.189)	$\Delta ln\left(Future_t^{Negative}\right)$	0.013	(0.235)
$\Delta ln(Spot)_{t-1}^{Negative}$	0.221 ***	(3.515)	$\Delta ln\left(Future_{t-1}^{Negative}\right)$	0.226 ***	(3.527)
$\Delta ln(Spot)_{t-2}^{Negative}$	0.209 ***	(3.270)	$\Delta ln\left(Future_{t-2}^{Negative}\right)$	0.204 ***	(3.077)
$\Delta ln(Spot)_{t-3}^{Negative}$	0.106	(1.593)	$\Delta ln\left(Future_{t-3}^{Negative}\right)$	0.105	(1.539)
$\Delta ln(Spot)_{t-4}^{Negative}$	0.128 *	(1.924)	$\Delta ln\left(Future_{t-4}^{Negative}\right)$	0.140 **	(2.080)
$\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$	0.674 ***	(5.750)	$\sum_{i=0}^{m} \hat{\delta}_i^{Negative}$	0.688 ***	(5.780)
$\Delta ln(Stocks)_t^{Positive}$	−0.618	(−1.180)	$\Delta ln(Stocks)_t^{Positive}$	−0.658	(−1.257)
$\Delta ln(Stocks)_{t-1}^{Positive}$	−1.040 *	(−1.957)	$\Delta ln(Stocks)_{t-1}^{Positive}$	−1.070 **	(−2.013)
$\Delta ln(Stocks)_{t-2}^{Positive}$	−1.157 **	(−2.057)	$\Delta ln(Stocks)_{t-2}^{Positive}$	−1.199 **	(−2.129)
$\Delta ln(Stocks)_{t-3}^{Positive}$	−0.251	(−0.459)	$\Delta ln(Stocks)_{t-3}^{Positive}$	−0.244	(−0.446)
$\Delta ln(Stocks)_{t-4}^{Positive}$	−0.075	(−0.131)	$\Delta ln(Stocks)_{t-4}^{Positive}$	−0.095	(−0.164)
$\sum_{i=0}^{m} \hat{\mu}_i^{Positive}$	−3.141 **	(−2.420)	$\sum_{i=0}^{m} \hat{\mu}_i^{Positive}$	−3.266 **	(−2.520)
$\Delta ln(Stocks)_t^{Negative}$	0.442	(0.812)	$\Delta ln(Stocks)_t^{Negative}$	0.449	(0.823)
$\Delta ln(Stocks)_{t-1}^{Negative}$	0.604	(1.116)	$\Delta ln(Stocks)_{t-1}^{Negative}$	0.612	(1.129)
$\Delta ln(Stocks)_{t-2}^{Negative}$	0.085	(0.155)	$\Delta ln(Stocks)_{t-2}^{Negative}$	0.098	(0.178)
$\Delta ln(Stocks)_{t-3}^{Negative}$	−0.168	(−0.299)	$\Delta ln(Stocks)_{t-3}^{Negative}$	−0.171	(−0.304)
$\Delta ln(Stocks)_{t-4}^{Negative}$	0.789	(1.434)	$\Delta ln(Stocks)_{t-4}^{Negative}$	0.808	(1.467)
$\sum_{i=1}^{m} \hat{\mu}_i^{Negative}$	1.752	(1.400)	$\sum_{i=1}^{m} \hat{\mu}_i^{Negative}$	1.796	(1.430)
$\Delta ln\left(Rig_t^{Gas}\right)$	0.090	(1.640)	$\Delta ln\left(Rig_t^{Gas}\right)$	0.068 **	(2.065)
$\Delta ln\left(Production_t^{Oil}\right)$	0.077	(1.397)	$\Delta ln\left(Production_t^{Oil}\right)$	−0.084 *	(−1.717)
$ln(CDD_t)$	0.006	(1.084)	$ln(CDD_t)$	−0.001	(−0.120)
$ln(HDD_t)$	0.005	(0.876)	$ln(HDD_t)$	0.003	(0.469)
$\Delta ln(Pipe\ Prices_t)$	−0.108	(−0.645)	$\Delta ln(Pipe\ Prices_t)$	0.078	(0.650)
$(Treasury\ Bond\ Rate)_t^{6-month}$	0.000	(0.190)	$(Treasury\ Bond\ Rate)_t^{6-month}$	0.001	(0.305)
ε_{t-1}^{Oil}	−0.064	(−0.076)	ε_{t-1}^{Oil}	0.100	(0.274)
ε_{t-2}^{Oil}	−0.015	(−0.037)	ε_{t-2}^{Oil}	0.232	(0.638)

Table 2. *Cont.*

Monthly Fixed Effects	Yes			Monthly Fixed Effects	Yes		
Observations F-statistic	387 12.43 ***			Observations F-statistic	313 12.33 ***		
Asymmetry Statistics:							
Variable	Long-term effect [+] (Positive Effects)			Variable	Long-term effect [+] (Positive Effects)		
	Coefficient	F-statistic	p-value		Coefficient	F-statistic	p-value
$ln(Spot_t^{Oil})$	2.397	4.455 **	0.036	$ln\left(Future_t^{Oil}\right)$	2.323	4.026 **	0.046
$ln(Stocks)_t^{Oil}$	0.548	0.005	0.946	$ln(Stocks)_t^{Oil}$	1.886	0.054	0.816
	Long-term effect [−] (Negative Effects)				Long-term effect [−] (Negative Effects)		
$ln(Spot_t^{Oil})$	−0.822	0.444	0.506	$ln\left(Future_t^{Oil}\right)$	−1.030	0.634	0.426
$ln(Stocks)_t^{Oil}$	−13.675	4.506 **	0.034	$ln(Stocks)_t^{Oil}$	−13.104	3.706 *	0.055
	Long-term asymmetry				Long-term asymmetry		
$ln(Spot_t^{Oil})$		0.805	0.370	$ln\left(Future_t^{Oil}\right)$		0.518	0.472
$ln(Stocks)_t^{Oil}$		1.159	0.282	$ln(Stocks)_t^{Oil}$		0.808	0.369
	Short-term asymmetry				Short-term asymmetry		
$ln(Spot_t^{Oil})$		10.200 ***	0.002	$ln\left(Future_t^{Oil}\right)$		10.210 ***	0.002
$ln(Stocks)_t^{Oil}$		4.755 **	0.030	$ln(Stocks)_t^{Oil}$		5.083 **	0.025

Note: t-statistics are shown in parentheses. *, **, and *** denote statistical significance at the levels of 10%, 5%, and 1%, respectively.

Panel B of Table 2 presents the empirical results of the ARDL model for the crude oil market. The results of Model (9) show that the coefficient estimate for the cumulative effect of oil spot price changes is 0.537 (t = 7.120), which is positive and statistically significant. However, the cumulative effect of oil rig changes ($\sum_{i=1}^{n} \hat{\rho}_i$) is significant at 1.070 (t = 1.910). In addition to the variable of gas rig changes, most control variables appear insignificant when we include the cumulative effect of oil rig changes. The results of Model (10) indicate that the cumulative effect of future oil price changes ($\sum_{i=1}^{m} \hat{\lambda}_i$) is significantly and positively correlated with the changes in the oil rig count. However, the cumulative effects of oil rig changes ($\sum_{i=1}^{n} \hat{\rho}_i$) remain significant.

Panel C of Table 2 presents the results of the NARDL model. Model (11) indicates that oil spot prices and oil stocks may have asymmetric long-term impacts on changes in oil rig counts. We find that its negative partial sum $\Delta ln\left(Spot_t^{Negative}\right)$ is significant, with the coefficient of $\sum\limits_{i=0}^{m} \hat{\delta}_i^{Negative}$ as 0.674 with t = 5.750, unlike the positive but insignificant one $\Delta ln\left(Spot_t^{Positive}\right)$, with the coefficient of $\sum\limits_{i=0}^{m} \hat{\delta}_i^{Positive}$ as 0.023 with t = 0.160. This suggests that in the long term the oil spot price affects changes in oil rig counts asymmetrically. However, we only find significant evidence $\Delta ln\left(Storage_{t-i}^{Positive}\right)$ of the positive impacts of oil stocks on oil rig counts. Based on these results, we find a long-term positive (negative) and significant effect of the oil spot price (oil stocks) on changes in oil rigs, confirming the significant short-term asymmetric effect of oil spot prices and oil stocks on oil rigs, while the long-term asymmetric effect on oil rigs is insignificant.

The findings from Model (12) indicate the long-term asymmetric effects of future oil prices and oil stocks on changes in oil rig counts. We report that its negative partial sum $\Delta ln\left(Future_t^{Negative}\right)$ is significant, with the coefficient of $\sum\limits_{i=0}^{m} \hat{\delta}_i^{Negative}$ as 0.688 with t = 5.780, unlike the positive but insignificant one $\Delta ln\left(Spot_t^{Positive}\right)$, with the coefficient of $\sum\limits_{i=0}^{m} \hat{\delta}_i^{Positive}$ as 0.029 with t = 0.200. This evidence indicates that oil spot prices asymmetrically affect changes in oil rig counts in the long term. However, we only find significant evidence $\Delta ln\left(Storage_{t-i}^{Positive}\right)$ of the positive impacts of oil stocks on oil rig counts. According to these results, we find that the long-term positive effects of future oil prices and negative effects of oil stocks on changes in oil rigs are statistically significant, confirming the significant short-term asymmetric effects of future oil prices and oil stocks on oil rigs, while the future oil prices and oil stocks show insignificant long-term asymmetric effects on oil rigs.

5.3. Asymmetric Dynamic Multipliers for Rig Counts

The analysis of the dynamic influences of the gas spot prices, future gas prices, and gas storage on gas rigs can be visualized using dynamic multipliers. Figure 5 demonstrates the cumulative dynamic multipliers generated from Models (5) and (6). These multipliers demonstrate the adjustment pattern of the gas rig count to its new long-term equilibrium due to unitary shocks in each variable. The dynamic multipliers are estimated based on the best-suited NARDL models reported in Table 1. For a given period, the positive (dashed blue line) and negative (dashed red line) change curves correspond to the adjustment of the gas rigs to positive and negative shocks, respectively. The asymmetrical curve (black line) reflects the differences in the dynamic multipliers associated with positive and negative shocks of each explanatory variable ($\delta_i^{Positive}$, $\delta_i^{Negative}$, $\lambda_i^{Positive}$, and $\lambda_i^{Negative}$).

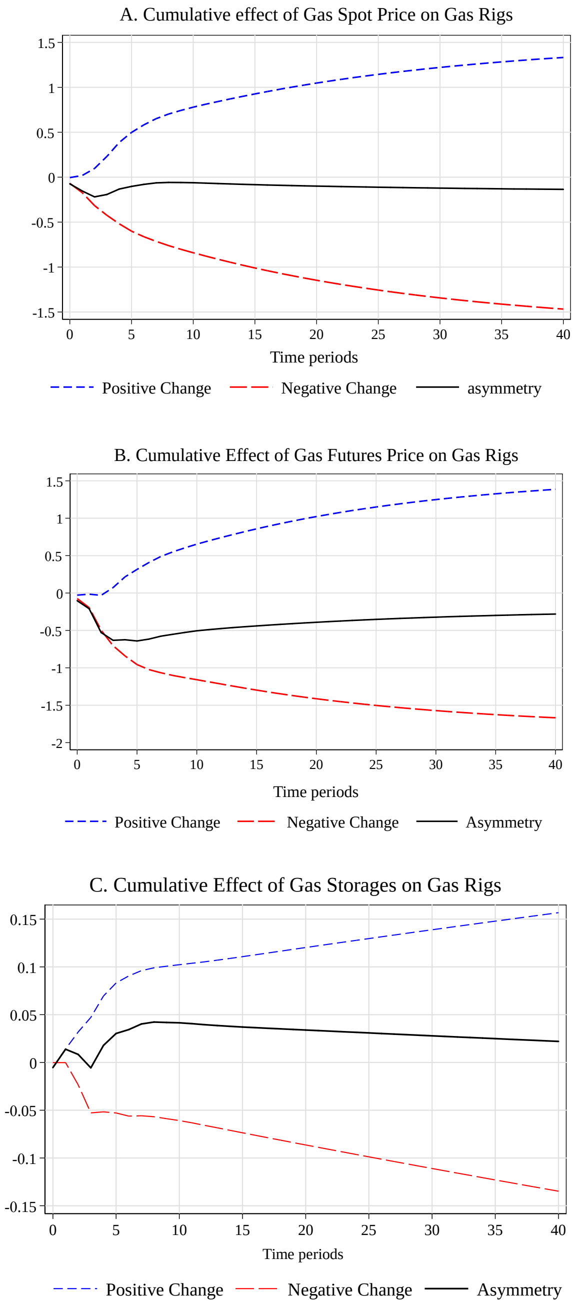

Figure 5. Dynamic multipliers for natural gas spot prices, future natural gas prices, and storage with respect to gas rig shocks.

Due to the asymmetric effect of gas spot prices on gas rigs, short-term adjustments have a negative inclination, as the magnitude of the negative effect of gas spot prices is greater than that of the positive effect, while long-term adjustments have lower asymmetry. Next, we find significant asymmetry regarding the asymmetric effect of future gas price on gas rigs, which tends toward a negative effect. Accordingly, the negative impact of future gas prices is greater than the positive one. In contrast with the gas spot and future prices, we find that the asymmetry of gas storages inclines toward the positive side. For crude oil rigs, Figure 6 illustrates the significant asymmetry caused by the negative effect of oil spot prices, future oil prices, and oil stocks. Specifically, the positive and negative effects are reversed in the long term, causing an obvious deviation in the asymmetry.

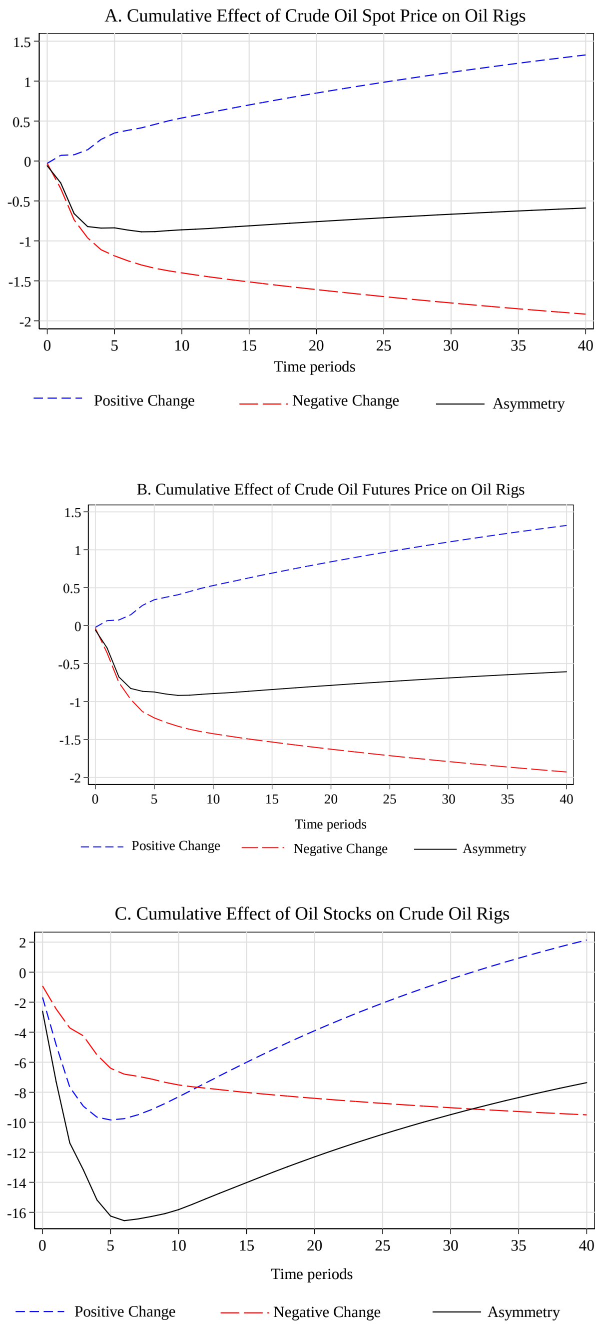

Figure 6. Dynamic multipliers for crude oil spot prices, future crude oil prices, and stocks with respect to crude oil rig shocks.

6. Conclusions

Our study fills a gap in research on producers' investment decisions by examining the correlation between drilling activity and prices. As developers consider all factors to reach the optimal investment decision, we consider a series of stop–go problems. Firms wait for a signal to start development (drilling). Upon receiving the signal, firms move into an irreversible process. Often, these signals change with changing technologies; this is particularly true for oil and natural gas, where development and drilling costs change depending on the type of system developed and the type of technology used by the firm. To the best of our knowledge, there are few empirical studies that have tested whether the real option theory can be applied to production field development. Additionally, our work highlights the most practically important issues concerning the development of optimal energy sources in the US and provides additional insights into the dynamic relationship between E&P activities and prices.

This paper empirically investigates the asymmetric effects of spot (future) prices and storage (stocks) on rig counts from January 1986 to May 2020 by focusing on the US natural gas and crude oil market. The NARDL model Shin et al. (2014) is used and provides a flexible and efficient framework by quantifying the transmission of positive and negative shocks in each of these variables to rig counts, and is able to model possible asymmetries in both short-term and long-term horizons [39].

Our empirical findings indicate that for the natural gas market there exist significant long-term asymmetric influences of gas spot (future) prices and storage on gas rigs, while for the crude oil market we observe significant short-term asymmetric effects of gas spot (future) prices and oil stocks on oil rigs. These findings suggest that oil companies are more sensitive to the price changes and associated costs than gas companies, and that when prices exceed a certain level companies are able to drill in areas where initial large wells were drilled. Furthermore, the assumption holds true in our findings that when more rigs are used for natural gas exploration the number of rigs used for oil exploration decreases, and vice versa. This finding is consistent with the supposition that companies have a fixed budget for lump sum drilling investment.

The cumulative effect of changes in future natural gas prices is significantly positively correlated with changes in the number of gas drilling rigs, implying that higher natural gas spot prices economically increase the number of natural gas drilling rigs. Furthermore, the cumulative effect of changes in natural gas storage is positive and statistically significant. It is confirmed that larger natural gas storage contributes significantly to changes in the use of natural gas drilling rigs. In contrast, the cumulative effect of oil rig changes remains significant. In addition, we find that oil spot prices and oil inventories have a long-term asymmetric effect on the number of oil rigs. From a long-term perspective, the oil spot price asymmetrically affects the changes in the number of oil rigs, while the long-term asymmetry between oil spot prices and oil rigs is not significant. Thus, a policy implication is that the nonlinear (asymmetric) effects of spot (future) prices and storage on rig counts in the US natural gas and crude oil markets should be taken into consideration during risk management in the context of rig drilling activity in the energy industry.

The interest rate significantly impacts both oil and gas drilling activities, confirming again that producers are more discreet in considering costs in their investment decision-making. In measuring the impact of weather conditions, which cause seasonal changes in drilling activity, it is surprising that the impact is not found to be significant overall. This may be due to our focus on the demand side. It would be more feasible to test whether extreme weather conditions, such as hurricanes and extreme temperatures, exert impacts on drilling construction.

The findings of this study are anticipated to help investors, market participants, and regulators clarify the critical factors to be considered in drilling activity. Moreover, the research findings obtained in this study can be used as a tool for forecasting and evaluation when predicting US crude oil and natural gas prices. The factors presented in this study can help decision-makers to more effectively predict the volatility of crude oil and natural gas prices, reduce investment risks, and obtain better returns. Future research could investigate how our models perform in other regions, and could include other relevant factors that may influence E&P activities in the industry, such as firms' financial performance and capacity utilization.

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