The Asymmetric Relationship between Conventional/Shale Rig Counts and WTI Oil Prices

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ABSTRACT

This work analyses the asymmetric response of conventional and shale oil rig counts to WTI oil price returns. Our analysis shows that the rig count time series exhibited a structural change after the oil glut of 2014. All series are non-stationary in each sub-period but not cointegrated. Therefore, after controlling for possible confounding factors, a vector auto regressive (VAR) model is set up. Our specification accounts for the possible role of oil production and distinguishes between positive and negative oil price changes. It is shown that shale and conventional rig counts reacted differently in each subperiod to signed changes in oil price. Subsequently, by evaluating the response of rig counts to oil price shocks, their intensity and duration over time, we observe that the shale oil rig count reacts more intensively to positive than to negative oil price changes. On the contrary, the conventional rig count exhibits a modest reaction only to positive price changes. Finally, we robustify our findings by focusing on the data of the Permian basin, on the one hand, and the Anadarko, Bakken, Eagle Ford and Niobrara, on the other hand, which are characterized by different patterns in the number of Drilled but not Completed wells.

Keywords: Shale rig count, Conventional rig count, Drilling trajectory, WTI price, VAR, Impulse Response Function, DUC

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1. INTRODUCTION

A drilling rig is a machine that creates holes in the earth subsurface to drill a new well to explore for, develop and produce oil. The number of active rigs has been fluctuating over the time. In the US, in the last decade, it has ranged from 818 in week 5 of 2011 (the first available observation in our dataset) up to 1,609 in week 41 of 2014, before falling to 316 in week 23 of 2016 and jumping back to 677 in week 52 of 2019, and then reaching a minimum of 172 in week 33 of year 2020 during the COVID-19 pandemic. The rig count can be related to changes in the price of crude oil, which has plummeted in the same period from a peak of \$112/bbl in April 2011 (weekly Cushing WTI spot price; EIA) to a low of \$28.1/bbl in February 2016, before reaching a record minimum of \$3.3/bbl in April 2020 during the first wave of COVID-19. The oil price can relate to the rig counts in several ways. The first obvious relationship refers to the link between rig counts, oil supply and oil price. A rise in the number of rigs can increase the supply of oil and thus affect the equilibrium price,

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even though the causality ordering can work also in the other direction. Changes in oil price can also affect the profitability of the investments in the industry, which in turn can affect decision-making to explore new fields, cultivate existing and prospective basins, and maintain, complete or suspend the production of existing wells. Thus, it is interesting and important for the understanding of the industry to assess, from a quantitative perspective, the relationship between rig counts, oil price and oil production. However, such a relationship cannot be established without taking into account the evolution of the oil industry over the last decade. Technical innovation of oil cultivation, namely, horizontal drilling and fracking, has allowed extracting oil entrapped in shale rock formations, named shale oil.[1] More precisely, shale oil is produced from shale wells undergoing first horizontal drilling and then a completion stage in which hydraulic fracturing, or fracking, is performed by means of a collection of equipment (such as high-pressure pumps, blenders and storage facilities) known as *frac spread*. In the US, shale oil has become the largest contributor to total oil production and has greatly increased the US oil supply. The US total crude oil production increased from 5,392 thousand barrels per day in February 2011 to 13,100 thousand barrels per day in march 2020 (then falling during the COVID-19 pandemic down to 9,700 in August 2020 and back to 11,500 one year later), mostly due to rise in shale oil production which reached a 67% share of total US crude oil production in 2019 (and 65% in 2020).

The variation in US oil prices and of the number of active oil rigs can be affected by the evolution over time of the US oil production due to structural changes in the industry, which witnessed the booming of shale production. This is what we consider here, testing whether the oil rig count/oil price nexus is affected by the nature of the oil extraction, distinguishing between conventional and shale oil rigs. We also investigate if an asymmetry exists in the relationship between oil rigs count and oil price when considering positive and negative oil prices and if such a relationship differs across types of rig counts, namely, conventional and shale oil rig counts. We do so by estimating and testing the difference in the delayed response of oil rig counts to the increase and fall of oil prices, distinguishing between the two types of oil rigs. We also consider the possibility that from the shale boom onward, the underlying relationship between oil rig counts and prices (considering both shale and conventional production and distinguishing between positive and negative changes) may have undergone a structural change. Indeed, from 2011 onward, on the one hand, the oil price series has experienced relevant drops throughout the period; on the other hand, the shale industry has seen a relevant reduction in its costs since its inception which has clearly affected the profitability of drilling new shale rigs. Thus, we test for the existence of structural changes in the long-run oil price/oil rigs relationship, as shown by breaks in the rig counts-oil price nexus, which highlight the existence and relevance of asymmetric impacts of oil price variations on rig count changes. In particular, the breaks accounts for structural changes in the oil industry, which witness relevant differences in the information transmission from market prices to production-related variables. Thus, if breaks would not be included in the analysis, the estimated economic links will be biased. Finally, we consider that the number of shale oil rigs can be influenced by oil price change, although also the opposite effect can occur, since oil rig counts affect oil supply and thus could impact on oil prices. Thus, we also study the reverse causality and feedback hypotheses of the oil price/oil rig nexus, testing for the impact on oil prices and oil production of rigs counts, distinguishing between conventional and shale oil.

1. It is common in the US terminology to refer to tight oil rather than shale oil, since the former is a more encompassing term with respect to the different geological formations producing oil from any particular well. In this article, for the sake of simplicity we shall refer to shale oil and use both terms as synonyms.

We show that the rig counts series exhibit two structural changes: the first after the oil glut of 2014, the second after the spread-out of COVID pandemic. This splits the analyses into three subperiods. In the first subperiod, from 2011 to the break date, oil price changes have hardly any impact on rig counts. In the second subperiod, from 2015 to 2019, the shale rigs show a higher response to oil price changes than the conventional ones. More precisely, by looking at the Impulse Response Functions (IRF) and Accumulated IRF originated from a Vector Auto Regressive (VAR) model, we show that the conventional rig counts respond only to positive changes in WTI returns, yet smaller than those for the shale oil rigs. The latter also respond reducing the number of rigs as the oil price return falls, but less so than the response to the positive ones. Production does not exhibit any feedback effect on prices. Lastly, the third subperiod, which is still ongoing, confirms the asymmetric response of shale versus conventional industry to oil price shocks; however, the evidence is less clear and still reflects the changing environment due to the ongoing pandemic. The findings of the second and third period highlight the importance of the structural changes that occurred over time in the oil industry, in particular in the shale one. The evolution of the production costs in shale industry, and its increasing relevance in the overall oil supply have affected the timing of oil supply response to price signals; this has a systematic and permanent effect in the industry that will also impact the future dynamic of the oil market. Finally, we check whether the difference between the drilling and the completion activities of the wells, which has risen in particular in the Permian basin, have influenced our findings. We show that the Drilled but Uncompleted (DUC) wells' dynamics has no relevant impact on our findings.

The paper is structured as follows. In the next section, we review the related literature, highlighting how the present paper extends and differentiates itself from the existing studies. Section 3 presents the data and includes preliminary analyses that justify the methodology introduced in Section 4. Section 5 includes and discusses the empirical results. Section 6 presents a robustness check, in which we split data across production regions and selected analyses are replicated. Conclusions and references close the paper. An Appendix includes a number of additional graphs.

2. BACKGROUND LITERATURE

There exists a vast literature that focuses on the oil industry from several perspectives, including the evaluation of the determinants of oil prices. However, far fewer analyses have focused on a quantitative assessment of the rig counts—oil price relationship. Kellogg (2014) sets up a real option model and empirically shows that drilling activity in Texas decreases as price uncertainty rises. Toews and Naumov (2015) consider the structure of the worldwide upstream sector of both oil and gas, studying the causal identification of shocks distinguishing between demand shocks, drilling activity shocks and drilling cost ones and showing that a rise in price shocks has a positive yet delayed effect on drilling activity and cost. Chen and Linn (2017) show that drilling rig use of oil and gas fields respond positively to oil and gas prices and that results hold also when controlling for changes in rig productivity. Anderson et al. (2018) show that Texas oil production does not react to change in price while drilling activity does, and formalize an Hotelling rule for drilling revenues that account for it. Ringlund et al. (2008) find a positive relationship between oil rig activity and the crude oil price. Newell and Prest (2019) investigate the price responsiveness of unconventional and conventional oil drilling in the United States, taking into account changes in wells productivity as well. Walls and Zheng (2022) econometrically estimate the oil supply of fracking and non-fracking production regions in the US. Iliescu (2018) finds that WTI oil prices and rig counts are cointegrated and identifies a bidirectional causality ordering. Ojukwu et al. (2020) consider the relationship between rig counts and Brent prices in Nigeria, showing a 3–4 month delay between Nigerian rig counts and oil prices. Espinasa et al. (2017) study the supply and demand drivers of oil prices in several countries, exploring the relationships between oil prices, rig count, oil production and world economic activity.

In a cointegration analysis, Zhang et al. (2018) evaluate the contribution of the US rig count, together with other explanatory variables, to Brent prices. Umekwe and Baek (2017) investigate the effects of oil prices and rig count on oil production in several US oil plays. Taneri et al. (2021) focus on the dynamics of the frac spread, showing that it is correlated to several variables, such as financial variables, oil stocks and rig count. However, rig count is less volatile than frac spread count. Apergis et al. (2016) analyse the long-term relationship between oil production, rig count and crude oil prices of six major oil producing regions in the US, while Apergis et al. (2017) focus on the relationship between well service rigs, operating rigs and oil and gas prices. Khalifa et al. (2017) quantitatively examine the oil price/rig count nexus, showing a delayed and nonlinear impact of changes in oil prices on rig count. However, the authors do not consider the causality of the oil latter is a key point of Apergis et al. (2021), which studies the relationship between rig count, oil price and oil supply in the US, distinguishing rigs based on their direction and considering positive and negative variations in prices, yet without testing for possible structural changes in the time series and for cointegration in each subsample, nor calculating the Impulse Response Functions in each subperiod. Other scholars have focused on drilling for shale gas wells. Mason and Roberts (2018) consider three margins on which natural gas producers may react to changes in natural gas prices: intra-well production rates, initial-production rate and well-drilling rates, showing that the decline rates of shale wells in Wyoming can be explained by pattern of falling natural gas prices. Ikonnikova and Gulen (2015) look at shale gas productivity changes, focusing on the relationship between gas prices and the completion practices of the industry (namely, the activities necessary for gas to flow after the drilling of a well). Scholars have also noted the dynamics of the DUC wells, which has been rising till spring 2020 then reducing again, investigating their impact on the supply and casting doubt on the drilling-production relationship. Mugabe et al. (2021) in particular[2] show that an increase in the number of DUCs plays a significant role in natural gas supply, and that the number of DUCs depends on drilling rig activity and futures prices of oil and natural gas.

In our work, we extend the existing literature focusing on the rig count oil price dynamics. We first identify three regimes associated with the breaks occurring in oil prices, shale rig counts, and conventional rig counts. Then, following the bound testing approach of Pesaran et al. (2001) adapted to the nonlinear auto regressive distributed lag (NARDL) model of Shin et al. (2014), we show that cointegration is not present at the subsample level. This induces us to model the first differences of the variables with a vector auto regressive (VAR) model accounting for the possible asymmetric impact of oil price and oil production changes, controlling for the impact of control variables, and analysing the impulse response functions (IRF). The IRFs allow us to assess the overall relationship between oil price and shale and conventional oil rig counts when the full system receives a shock to prices. Finally, we perform a robustness check taking into account the possible role played by the DUCs in the oil price-rig count relationship, focusing on the data of specific regions characterized by different DUCs dynamics and shale oil production, namely, the Permian, on the one hand, and the Anadarko, Bakken, Eagle Ford and Niobrara, on the other hand. Our results extend and differ from those in Apergis et al. (2021) for two different reasons. First of all, the results in Apergis et al. (2021) are unreliable and the evidence much weaker, as shown in Ewing et al. (2022); this supports our methodological choices. Second, by allowing for breaks, we account for the existence of structural changes in the relation between rig counts and oil prices. In fact, the asymmetric reaction of rig

2. See also the references reported in that paper about the impact of DUCs on the wells' completion activities.

counts to oil price variations emerges in a strong way only when removing a first period, up to 2014, characterized by a sharp increase in shale oil supply, and also removing the COVID-19 period, with drop in oil demand and high uncertainty, partly due to COVID-related policies.

3. DATA AND PRELIMINARY ANALYSIS

3.1 Data sources and data description

The main variables we adopt are the weekly West Texas Intermediate (WTI) crude spot oil prices,[3] the onshore crude oil field production, and the weekly observations of the oil rig count. WTI oil prices have been recovered from the Federal Reserve Bank of St. Louis database (FRED),[4] oil production data come from the US Energy Information Administration (EIA),[5] while the rig count series is provided by Baker Hughes' weekly reports[6] on US drilling activities. The Baker Hughes report contains the time series of rigs counts for each basin in the US, providing detailed data on the oil rigs, classifying them into oil, gas, and miscellaneous; moreover, the reports also classify the rig counts according to their trajectories, dividing them into vertical, directional and horizontal.

Given the purpose of the present study, we aggregate the rigs into two categories using the rig trajectory: vertical and directional[7] are considered conventional oil drilling, which we term as *conventional oil rigs*, and horizontal rigs are considered as related to nonconventional oil drilling techniques, which we call *shale oil rigs*. This classification is justified by the different drilling techniques adopted to extract oil. The conventional drilling technique, widely adopted in the industry, involves the use of a vertical well that aims directly at a target beneath it. In contrast, horizontal drilling followed by hydraulic fracturing has allowed the extraction of oil from layers of sedimentary rock characterised by low permeability, expanding the ability of producers to profitably recover oil from low-permeability geologic plays, mostly shale. The entire sample considered in this paper starts on 4th February 2011 and ends on 21st January 2022, yielding a total of 573 observations.

3.2 Descriptive analysis

Figures 1 and 2 report the evolution of variables' levels and differences (or relative changes), respectively. Looking at the WTI oil prices, we observed a drop during the last semester of 2014.

3. Wellhead prices can diverge from WTI because of mid-stream constraints (Agerton and Upton (2019), Walls and Zheng (2020), McRae (2017)). Even if the wellhead price might more accurately reflect the flow of revenues accruing from each shale well, we cannot rely on such a data for our analyses since it is available only on a monthly basis and is not aggregated per basin. Nevertheless, we point out that wellhead oil prices display little dispersion (Agerton et al. (2021)) and mostly referring to the first subperiod. For this reason, we believe that this should not affect the results of our analyses, in particular for the second and third subperiods.

4. https://fred.stlouisfed.org

5. https:/www.eia.gov

6. https://rigcount.bakerhughes.com/na-rig-count/

7. Directional drilling is mostly used to avoid underground obstacles or for environmental reasons; it could be regarded as a mixture of vertical and horizontal drilling, even though it was traditionally associated with vertical drilling. It is disputable whether data on directional drilling should be taken as a proxy of conventional or unconventional wells. The latter approach has been followed for instance in Apergis et al. (2021) and in Newell et al. (2019), who focus on unconventional wells in Texas. We follow here Newell and Prest (2019), who classify directionally-drilled wells as conventional, considering a larger sample of wells in five US states (Texas, North Dakota, Oklahoma, Colorado, California). Note, however, that the number of directional rigs is very limited and therefore the classification does not influence the results of our analyses.

Figure 1: Plots of the variables in level

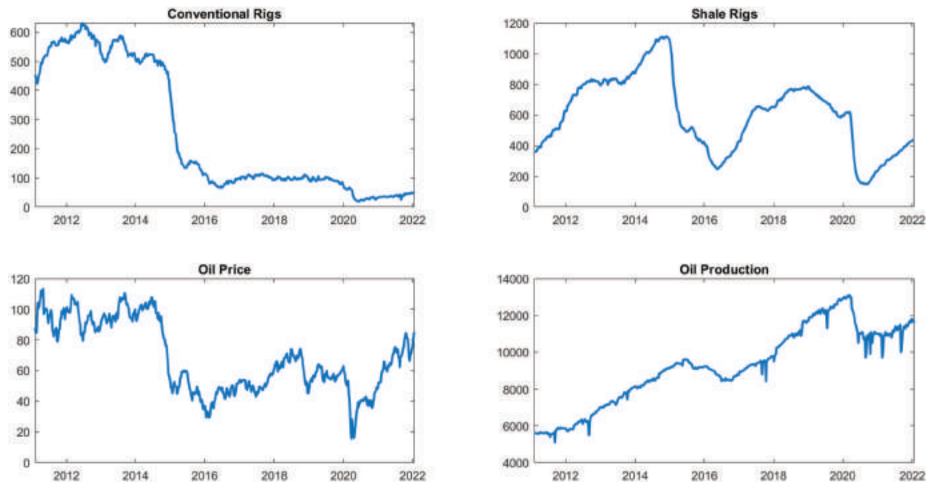
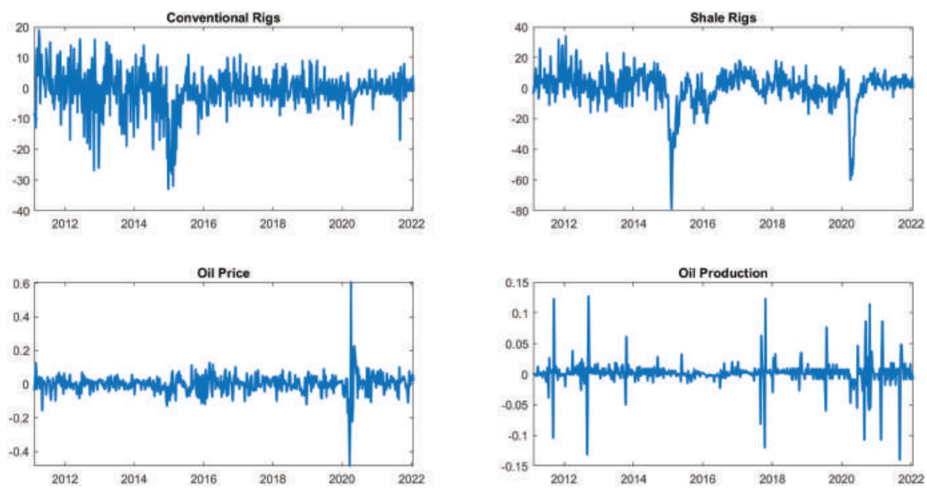


Figure 2: Plots of the variables in first difference



This drop, commonly called *oil glut*, was mainly driven by the explosion of shale oil production that has sensibly increased the supply, coupled with the OPEC decision to maintain stable production levels rather than decrease them. Both the shale and conventional rigs are characterized by a drop in the same period, even if this lagged by a few weeks. Specifically, the WTI dropped from a peak level of 105.23 USD registered in the last week of July 2014; this was followed by a drop in the conventional rigs six weeks later on 5th September 2014 and a drop in the shale rigs only 18 weeks after the WTI oil price drop in the last week of November. This event can be considered a regime shift for both the oil price and for the rig counts towards new, lower levels. In particular, while the conventional rigs maintained a more stable pattern, with no tendency to revert toward the pre-oil glut level, the shale rigs saw a subsequent increasing trend from 2016 to the last quarter of 2018. Oil production is characterized by an increasing trend, except for a local contraction between mid-2015 and mid-2016. In 2020, COVID-19 severely impacted the oil sector, with a contraction in active rigs, particularly evident for shale rigs. In addition, oil production drops by more than 20%, and only in the second half of 2021 does it appears to be on the rise. Lower production levels in 2021 compared to the pre-COVID-19 period, combined with problems in the distribution chain, affected the evolution of the oil price. In fact, from the minimum of about 15 USD observed in March 2020, the price increased up to the end of our sample, reaching above 90 USD, the maximum level since the end of 2014.

Moving to the variables in the first difference, it can be observed that the two types of rigs reacted differently to the 2014 negative oil shock. While the number of shale oil rigs is more sensitive, with a more pronounced drop, the conventional ones are more volatile and require a longer period to revert to the unconditional mean. A similar behavior appears after the COVID-19 outbreak, with a striking impact on the changes in the number of shale rigs.

To proceed with the analyses, it is fundamental to determine whether the series of interest are stationary or characterised by a unit root. Table 1 reports a selection of tests for all variables of interest. In the first three lines, we focus on standard tests for unit roots: the Dickey-Fuller, Phillips-Perron and KPSS tests. The three tests are consistent for almost all variables in identifying the presence of a unit root. The only exception is the KPSS test in the case of shale rigs which is stationary but only if we use the 5% confidence level (at the 1% confidence level, all variables are characterised by a unit root). However, the graphical analyses of the levels (Figure 1) suggest that the series, at least those of the rig counts, could be characterised by structural breaks in the deterministic components. Therefore, we proceed with the analyses of stationarity by means of tests robust to the presence of breaks in the trend and/or intercept. We first consider the test proposed by Perron (1989) that allows for a single break in both the trend and the intercept and originates from an innovation outlier (so the break is not instantaneous). Furthermore, we endogenously determine the break date by focusing on the minimum value of the Dickey-Fuller test statistic; see Perron and Vogelsang (1992). Again, we find evidence of heterogeneity across series, as the oil log-prices, the oil log-production and the shale rig counts seem to be nonstationary, while the conventional rig counts are stationary. Additionally, the break date for all series is located in the last quarter of 2014; the break date occurs during the oil glut period, coherently with the graphical analysis (see Figures 1 and 2). The existence of the COVID-19 pandemic, which had a relevant impact on the oil market,

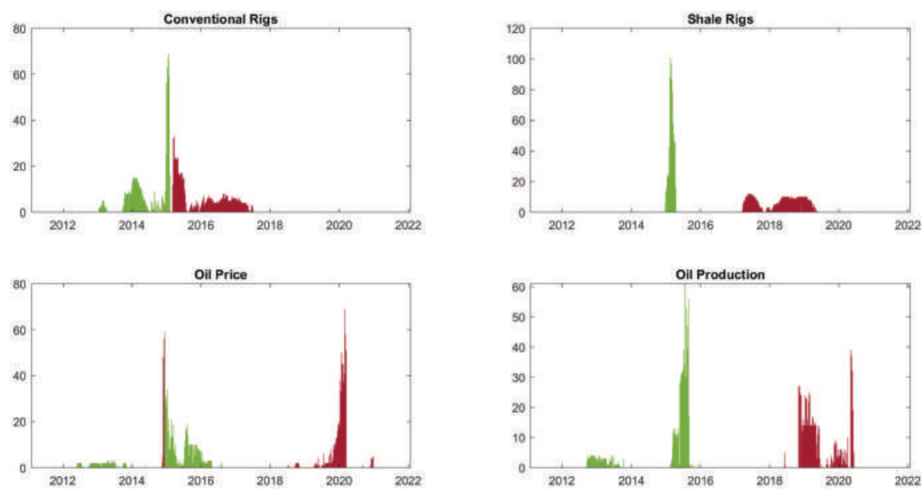
Table 1: The table reports results for several unit root tests.

	Δlog WTI	Δlog Oil Prod.	Δ Shale rigs	Δ Conventional rigs
ADF (p-value)	0.282	0.434	0.251	0.160
PP (p-value)	0.181	0.494	0.439	0.140
KPSS (test)	0.304	0.371	0.180	0.433
Breakpoint (p-value)	0.498	0.839	0.731	<0.01
Date	31/10/2014	07/09/2012	28/11/2014	05/12/2014
Two-break (test)	–30.656	–45.902	–2.132	–11.208
Date-1	12/12/2014	10/07/2015	20/02/2015	16/01/2015
Date-2	26/08/2016	09/11/2018	15/06/2018	26/08/2016

In detail, we include the following cases: row *ADF* reports the p-values of the Dickey-Fuller test, with automatic selection of the number of lags using BIC and deterministic components included only if statistically significant; in row *PP*, we provide the p-value for the Phillips-Perron unit root test with Bartlett kernel and Newey-West bandwidth, and deterministic components are included only if they are statistically significant; *KPSS* includes the KPSS test statistic computed with Bartlett kernel and Newey-West bandwidth, and deterministic components are included only if statistically significant—the critical values for the null of stationarity are equal to 0.216 at the 1% confidence level and 0.146 at the 5% confidence level; *Breakpoint* and *Date* refer to the Perron test for unit root in the presence of a break in the deterministic components (both trend and intercept)—we report the p-value associated with endogenous detection of the break date using the minimum of the Dickey-Fuller statistic, as well as the identified break date; *Two-break*, *Date-1* and *Date-2* refer to the Lee-Strazicich unit root test with two breaks in the deterministic components (both trend and intercept) and endogenous selection of the break dates by the minimisation of the Dickey-Fuller statistic—we report the ρ test statistics as well as the identified break dates—critical values are equal to –52.550 at the 1% level and –45.531 at the 5% level. In all tests adopting lags, we identify the optimal lag by the BIC criterion using a maximum lag equal to 13 (that is, one quarter) in line with the findings in Khalifa et al. (2017).

suggests that two breaks could be present: the first during the oil glut and the second in the first phase of COVID-19 diffusion. Thus, we employ the Lee and Strazicich (2003) unit root test, which allows for the existence of two breaks. Again, the break affects both the trend and the intercept, and we endogenously identify the break dates by minimising the Dickey-Fuller statistic. We also impose that the subsamples identified by the break dates have a minimum length equal to 10% of the data (i.e., 57 observations). The test outcomes shown in Table 1 suggest that oil log prices and both rig count time series are nonstationary, while the oil log production is stationary at the 5% confidence level but not at the 1% level. Finally, some heterogeneity is apparent in the identified break dates, similar to the test with a single break; nonetheless, in three out of four cases, the breaks are identified between the end of 2014 and the first months of 2015, just after the oil glut. Summarising our findings, we assume the existence of a unit root in all series, together with the presence of at least one structural break. To identify the break dates, we analyze the Lee and Strazicich (2003) test statistics computed across all possible break date pairs (these data are a by-product of the Lee and Strazicich procedure). Out of all possible cases (that is, pairs of possible break dates), we focus on the 1% of cases with the highest negative values of the test, computing frequency histograms of the associated break dates; see Figure 3. In particular, all series show a spike during or after the oil glut, while less homogeneity is visible for the occurrence of the second break date. While rig counts seem unaffected by the COVID-19 period, the oil price and oil production are more sensitive to the pandemic, especially the oil price, which has a second spike in March 2020.

Figure 3: Frequency of possible break dates under the Lee-Strazicich unit root test.



The first break dates are in green, and the second break dates are in brown.

Based on the evidence shown, in the next section we model the long-term relationship between variables characterised by unit roots and breaks using two break dates, occurring in the fourth quarter of 2014 and in the first quarter of 2020, which span the oil glut and the COVID-19 outbreak. We prefer not to report a precise break date due to the heterogeneity across the analyzed series. Our final objective is to verify whether the interdependence among variables has changed during the sub-periods. Note that, given the uncertainty in the break date identification, as shown in the previous analyses, and given the heterogeneous behavior of the series around break dates, we will apply both rolling approaches as well a subsample analysis in which the observations in the break dates periods will be excluded from the estimation sample. This last case allows to concentrate on the interdependence between variables, excluding periods of transition between two different states of interdependence.

Before this, we provide descriptive statistics for the first difference or relative changes; see Table 2. All variables show evidence of clear deviation from normality. Furthermore, additional analyses[8] show evidence of serial correlations in all variables (differences or logarithmic differences). For rig counts, this evidence is consistent with the findings of Khalifa et al. (2017), which document the impact of lagged values for rig counts up to 13 weeks (i.e., roughly one quarter).

Table 2: Descriptive statistics of the variables.

	Δlog WTI	Δlog Oil Prod.	Δ Shale rigs	Δ Conventional rigs
Mean	<0.000	0.001	0.135	–0.705
Median	0.001	<0.001	1.000	<0.001
Min	–0.212	–0.061	–79.000	–33.000
Max	0.263	0.055	34.000	19.000
St.Dev.	0.026	0.009	11.803	6.801
Skew.	0.538	–0.537	–2.077	–1.030
Kurt.	26.605	19.807	9.254	3.445

The table refers to the four variables of interest, WTI prices, oil production and shale and conventional rigs, expressed in their log-difference or first difference as reported in the first row, over the full sample.

3.3 Control Variables

We introduce in our analyses a set of economic and financial variables with the aim of removing the possible presence of common factors that could impact the relationship between rig counts, oil price and oil production. A similar approach has been used, for example, in Khalifa et al. (2015, 2017), among others. Three types of variables have been considered: economic variables, indicators of financial stress and variables related to the bond/credit market.

Within the first category, we include the Trade-Weighted US Dollar Index Advanced Foreign Economies (TRADE) and the S&P 500 Index (GSPC). The former allows monitoring of the effect of the reference currency (dollar) used in pricing the oil relative to other currencies. The latter contains 500 of the largest stocks traded on the New York Stock Exchange and NASDAQ and is generally used to monitor financial market evolution.

Moving to the indicators of financial stress, we consider the St. Louis Fed Financial Stress Index (STLFSI2), the CBOE Volatility Index (VIX) and the National Financial Conditions Index (NFCI). The first measures the degree of financial stress in markets and is provided by the Federal Reserve Bank of St. Louis. The average value of the index is designed to be zero whenever the financial market conditions are normal, while a value below zero represents a financial market stress and vice versa. The VIX, instead, is a market index that represents the market's expectations for volatility over the next 30 days, providing a measure of market risk and investor sentiment. Finally, the Chicago Fedâ€™s National Financial Conditions Index provides a comprehensive weekly update on US financial conditions in money markets, debt and equity markets, and traditional and shadow banking systems.

The variables related to the bond/credit market are the Effective Federal Funds rate (EFFR), the 10-year Treasury Constant maturity rate (DGS10) and the TED spread (TEDRATE). The EFFR consists of domestic unsecured borrowing in US dollars by depository institutions. The

8. Additional descriptive analyses are available upon request.

DGS10 represents the annual average of the interest rate on 10-year Treasury bonds. The TED spread is defined as the difference between the interest rates on interbank loans and on short-term US government debt, the so-called T-bills.

All data were collected from the Federal Reserve Bank of St. Louis database, in the same sample adopted for oil price, oil production and rig counts.[9]

4. MODELING STRATEGY

4.1 Bound testing for cointegration

Our objective is to identify the asymmetric impact of oil price and oil production on the evolution of rig counts and to analyse the interdependence between these variables over different market phases. We first adopt the modeling strategy of Apergis et al. (2021). Therefore, we introduce, for both conventional and shale rigs, a NARDL specification (see Shin et al. (2014) for additional details on the model) and test for cointegration within this model. Let us define the variable of interest as y_t; in our case, it is either the number of shale rigs or conventional ones. Moreover, let us denote by p_t and q_t the oil log prices and the log production, respectively. In the model, we also include the covariates, which are transformed, when needed, to make them stationary. We denote by $x_{l,t}$ the l-th covariate that enters the equation lagged (and $x_{l,t}$ is stationary). The NARDL model reads as follows:

$$\begin{aligned}\Delta y_t &= \mu + \alpha t + \rho_S y_{t-1} + \beta_{p,-} p^{-}_{t-1} + \beta_{p,+} p^{+}_{t-1} + \delta_{q,-} q^{-}_{t-1} + \delta_{q,+} q^{+}_{t-1} \\ &\quad + \sum_{j=1}^{m} \gamma_{1,j} \Delta y_{t-j} + \sum_{j=0}^{m} \gamma_{2,j} \Delta p^{-}_{t-j} + \sum_{j=0}^{m} \gamma_{3,j} \Delta p^{+}_{t-j} \\ &\quad + \sum_{j=0}^{..} \gamma_{4,j} \Delta q^{-}_{t\aleph j} + \sum_{j=0} \gamma_{5,j} \Delta q^{+}_{t\ \ j} + \sum_{l=1} \theta_l x_{l,t\ \ 1} \varepsilon_t\end{aligned} \quad (1)$$

where Δ denotes the difference operator (i.e., $\Delta p_t = p_t - p_{t-1}$), $\Delta p_t^{+} = \max\left(0, \Delta p_t\right)$ with Δp_t being the change in target variable, $\Delta p_t^{-} = \min\left(0, \Delta p_t\right)$, and where $p_t^{+} = \sum_{i=1}^{t} \Delta p_i^{+}$ and $p_t^{-} = \sum_{i=1}^{t} \Delta p_i^{-}$ are the cumulated signed components. The equations include both an intercept and a trend that enter the cointegration (long-run or level) equation. With respect to the lag structure, that is, the choice of m, based on the evidence in Khalifa et al. (2017) that suggests the relevance of a quarterly lag when modeling the rig number, and to reduce the number of parameters, we proceed as follows: first, we fix $m = 13$, thus including the data covering roughly one quarter; then, we adopt the following restricted specification (displayed for the case of negative oil price returns—for other cases, the structure is equivalent):

$$\sum_{j=0}^{m} \gamma_{2,j} \Delta p^{-}_{t-j} = \gamma_{2,0} \Delta p^{-}_{t} + \gamma_{2,1} \Delta p^{-}_{t-1} + \hat{\gamma}_{2,M} \sum_{j=1}^{4} \Delta p^{-}_{t-j} + \hat{\gamma}_{2,Q} \sum_{j=1}^{13} \Delta p^{-}_{t-j}, \quad (2)$$

where we have specific parameters associated with the contemporaneous impact, the lagged weekly impact, the monthly impact (proxied by the last four weeks) and the quarterly impact; similar parametrisations are used for all components (summations) appearing in the model in equation (1). In unreported results (available on request), we verified the significance of the NARDL parameters referring to the monthly and quarterly lags. Joint Wald tests for parameter significance reject the

9. Descriptive statistics and figures for control variables are available upon request.

null hypothesis of zero coefficients in the equations for conventional and shale rig counts, thus supporting the introduction of lags up to 13 weeks.

In the NARDL setting, Shin et al. (2014) suggest testing the hypothesis of cointegration following the proposal of Pesaran et al. (2001), that is, the bound testing approach. Such a choice provides flexibility to the testing framework as it is viable even in situations where not all series are characterised by clear evidences of unit roots, exactly the situation that occurs in our case. We also note that the same modeling and testing strategy was adopted by Apergis et al. (2021), leading in their case to the identification of the presence of cointegration. We reconsider their analyses and first test for cointegration at the full sample level.

We report in Table 3 the results of bound testing for cointegration in the NARDL model: the existence of cointegration is associated with the specific outcomes of a joint test on the parameters of the level variables (an F-test) and of a test on the parameter of the lagged level of the dependent variable (a t-test). The table reports the test statistics and the bounds. A value of the F-test statistic on the left of the lower bound excludes the possible existence of cointegration, while a value between the bounds is inconclusive. In contrast, a value on the right of the upper bound is coherent with the possible existence of cointegration, but this needs to be accompanied by a verification via the t-test. For the latter, again a value between bounds is inconclusive, and a decision can be made when the test statistic falls outside the bounds. Following Pesaran et al. (2001), we report the test for different specifications of the model, that is, with unrestricted intercept and no trend (case III in the cited paper), restricted trend and unrestricted intercept (case IV) and unrestricted trend and intercept (case V).

We first focus on the conventional rig series. The F-test for cointegration suggests absence of cointegration if we consider the 1% confidence level, while it is inconclusive when using the 5% or 10% confidence levels. This finding is not affected by the specification adopted for the deterministic components. Consequently, the evaluation of the t-test becomes irrelevant. When considering the shale rigs, the evidence is clearly in favour of cointegration among variables, irrespective of the specification adopted for the deterministic terms. Our results are clearly in contrast with those of Apergis et al. (2021), although they did not include covariates in the model and focused on a shorter sample. Table 3 also reports the bound tests evaluated with the same sample adopted by Apergis et al. (2021), with and without the inclusion of covariates (to be fully consistent with the paper cited). Results on data excluding most of 2019 and the COVID-19 period are more heterogeneous across model specifications for the conventional rig time series, while the evidence is stronger in favour of cointegration for the shale rig time series. Notably, the introduction of covariates does not alter the finding.[10] Beside the simple evaluation of bound testing on the full sample, we also focus on a subsample evaluation of the cointegration. Such a choice is coherent with the evidence of the stationarity tests that suggested the possible presence of breaks in the series, due either to the oil glut or to the pandemic. We opt here for a rolling bound testing analysis of cointegration given the uncertainty about the break date. In Figure 4, we report the F-statistic for the bound testing in case V, and with an evaluation window of 104 observations (about 2 years). Case V is the most flexible as it allows for unrestricted trend and intercept. Notably, few periods support the possible presence

10. Our results differ from those reported in Apergis et al. (2021) and this may depend on a number of reasons (the impact of covariates excluded given the results reported in Table 3): first of all, we used a log-transformation for the oil prices and oil production but not for the rig counts, while Apergis et al. (2021) transform all variables into natural logarithms; second, the estimates in Table 4 of Apergis et al. (2021) used to build the bound tests report, coherently with equations 1–6–7–8 of Apergis et al. (2021), the presence of both lagged levels and the error correction term; third, they use a single while we include lags up to one quarter.

Table 3: Bound testing approach for cointegration.

	F-test	T-test	F-test	T-test
	Conventional		Shale	
	Full sample			
Case III	2.977	–3.388	5.735	–5.132
Case IV	2.973	–3.779	5.775	–5.566
Case V	3.521	–3.779	6.882	–5.566
	up to 22/03/2019			
Case III	3.689	–3.989	4.132	–4.227
Case IV	3.292	–4.012	4.046	–4.601
Case V	3.819	–4.012	4.827	–4.601
	up to 22/03/2019 without $x_{l,t}$			
Case III	3.890	–3.833	4.692	–4.368
Case IV	3.450	–3.838	4.440	–4.696
Case V	4.129	–3.838	5.295	–4.696

	10%		5%		1%	
Critical values	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F-test k=4 Case III	2.45	3.52	2.86	4.01	3.74	5.06
T-test k=4 Case III	–2.57	–3.66	–2.86	–3.99	–3.43	–4.37
F-test k=4 Case IV	2.68	3.53	3.05	3.97	3.81	4.92
F-test k=4 Case V	3.03	4.06	3.47	4.57	4.40	5.72
T-test k=4 Case V	–3.13	–4.04	–3.41	–4.36	–3.96	–4.96

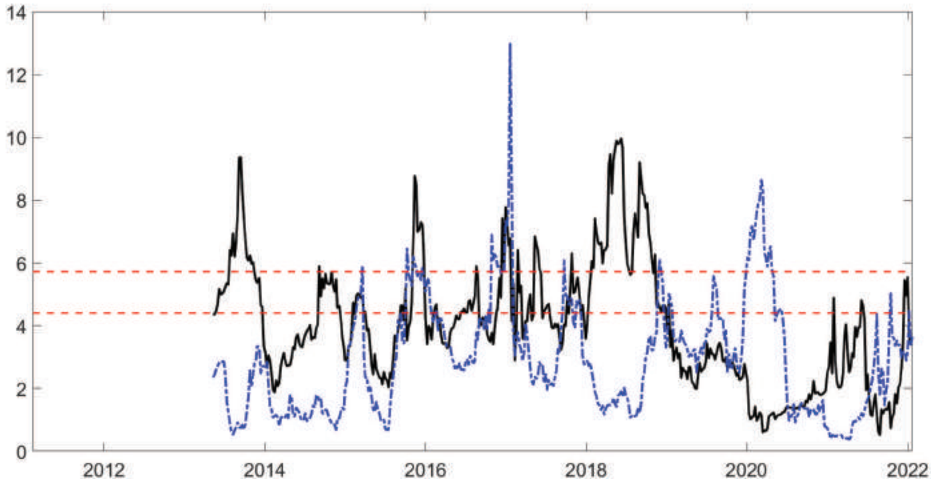
The upper panels report the two tests for cointegration following Pesaran et al. (2001): namely, an F-test to evaluate the null hypothesis that all coefficients appearing in the level relationship included in equation (1) are jointly null, and then a t-test to verify the significance of the coefficient for the lagged level of the dependent variable. The table reports the test statistics for three cases (III, IV and V) for both the conventional and shale rigs: case III includes an unrestricted intercept and no trend, case IV a restricted trend and an unrestricted intercept, and case V unrestricted trend and intercept. Furthermore, we focus on two different periods: the full sample available to us and the sample considered in Apergis et al. (2021); for the latter, we also report results with and without the inclusion of covariates. The lower panel reports the critical values for the bound test for different confidence levels. Cases IV and V for the t-test are equivalent. If the test statistic is to the left of the lower bound, we reject the null and there is no cointegration among the variables. If the test is above the upper bound, we are in favour of cointegration. When the test statistic is within the two bounds, the test is inconclusive, and further evaluation of the cointegration of the variables (excluding the dependent one) should be made. If the F-test leads to a rejection of the null, there is no need to verify the outcome of the t-test. The latter is relevant only if the first test suggests the presence of cointegration, which has then to be validated by the second test. If the t-test rejects the null, there is no cointegration even if the F-test goes in that direction; see Pesaran et al. (2001) for additional details.

of cointegration, while longer time spans suggest the absence of cointegration. Similar outcomes are obtained by considering different window sizes and different test cases.[11]

The rolling approach provides interesting evidence suggesting that interdependence between variables is, most of the time, not associated with the existence of cointegration. As a final check, we follow the approach of Carrion-i Silvestre and Sanso (2006), which introduces a cointegration test consistent with the possible presence of a break that impacts both the deterministic components and the cointegration coefficients. The break date is endogenously identified, setting the minimum subsample length (either before or after the break) equal to 104 observations (2 years), using the most flexible parameterisation, that is, Model E of Carrion-i Silvestre and Sanso (2006), where a trend is included and the break impacts on the cointegration coefficients, and evaluating the test under the assumption that regressors are not strictly exogenous (see Carrion-i Silvestre and

11. Results are available on request.

Figure 4: Bound testing approach for cointegration: F-statistic computed over a rolling window of 104 observations (2 years) under case V (unrestricted trend and intercept) for both the conventional (continuous black line) and shale (dashed blue line) rigs.



The two straight dashed lines are the bounds for cointegration: a statistic below the lower bound indicates absence of cointegration, while a statistic above the upper bound is in favour of cointegration; values between the bounds are inconclusive.

Sanso (2006) for details). Table 4 reports the results, which clearly reject the null hypothesis of cointegration for both the conventional and shale rig counts.

Table 4: Test of Carrion-i Silvestre and Sanso (2006) for cointegration in the presence of a break in the cointegration coefficients.

	Conventional Rigs	Shale Rigs
Test-statistic	0.388	5.117
Break date	16/01/2015	30/01/2015
C.V. $\lambda = 0.3$	1%—0.0393	5%—0.0570
C.V. $\lambda = 0.4$	1%—0.0329	5%—0.0454

Constant and trend included. Minimum subsample length: 104 observations. λ is the fraction of observations before the break date. For the break dates reported, $\lambda \approx 0.36$. The break date has been determined endogenously. The critical values reported allow for the evaluation of the null hypothesis of cointegration. Large values of the test statistic suggest the absence of cointegration.

In particular, the break date was identified at the beginning of 2015, just after the oil glut. When combining all the evidence collected, we can conclude that no cointegration is evident among the modeled variables. Consequently, we focus on dynamic models built on the first difference of the variables. In addition, due to the presence of structural breaks in the variables of interest, we proceed with the analysis of subsamples. We separate the first part of our data up to the oil glut from the subsequent period. Then, we also account for the impact of the pandemic and consider three subsamples. Furthermore, given the relevant changes and the instability observed in the variables of interest, as well as the associated heterogeneity in the identification of the break data, in order to focus on the variables' interdependence outside the break period, the subsamples we consider are not contiguous. This strategy allows the detection of structural changes in the interdependence and at the same time limits the possibility that the instability around break dates impacts on the parameter estimation. The specific periods considered are detailed further below in the empirical analysis section.

Note that implementing such a modeling strategy gives rise, in each subsample, to a system of equations wherein, besides the changes in the shale and in the conventional rigs, the changes in the log levels of both the oil price and oil production are also included. The system of equations is similar to a structural vector auto regressive (SVAR) model with the exception that the explanatory variables for the oil price and production are decomposed into their signed counterparts, as explained in the subsection below.

4.2 A VAR-type model

In each subsample, in the absence of cointegration, the NARDL model in equation (1) collapses to a linear model across stationary variables (changes and returns), including contemporaneous relations. Therefore, the system including the rig counts change (conventional and shale), as well as the oil price returns and the relative changes in oil production, becomes similar to a structural VAR. We concentrate on the reduced form representation focusing on the dynamic interdependence between variables and on the role of lagged signed oil price changes on the changes in rig counts. In order to measure the different reactions of oil rigs to increasing and falling oil prices, we first filter out the common factors impact from our variables of interest, as proxied by the set control variables defined in Section 3.3 using the following linear model:

$$\mathbf{y}_t = \boldsymbol{\mu} + \boldsymbol{\beta}\mathbf{F}_{t-1} + \tilde{\mathbf{y}}_t, \tag{3}$$

where: $\mathbf{y}_t$ is the four-dimensional vector containing the change in conventional rig counts ($y_{Co,t} = \Delta ConventionalRigs_t$), the change in shale rigs ($y_{S,t} = \Delta ShaleRigs_t$), the change in oil log-prices ($y_{O,t} = \Delta \log WTI_t$) and the change in oil log-production ($y_{P,t} = \Delta \log OilProd_t$); $\boldsymbol{\mu}$ is a vector of intercepts; $\mathbf{F}_t$ is the K-dimensional vector including the K control variables; $\boldsymbol{\beta}$ is the $4 \times K$ matrix of coefficients monitoring the impact of control variables on the variables included in $\mathbf{y}_t$; $\tilde{\mathbf{y}}_t$ is the vector of the variables of interest filtered from the impact of control variables and with zero mean. The specification above differs from those in the previous sections. We follow this strategy to simplify the subsequent evaluation of IRFs which are based on a simulation approach, as we shall discuss below. Filtering out control variables at this stage also corresponds to a removal from the target variables of the predictable component associated with exogenous regressors, a procedure that allows one to focus on the unpredictable movements of rig count changes.

In the second step of our analysis, we model the filtered variables in $\tilde{\mathbf{y}}_t$ by using a specific VAR-like specification. Let us start by introducing a standard VAR model with p lags:

$$\tilde{\mathbf{y}}_t = \boldsymbol{\Phi}_1\tilde{\mathbf{y}}_{t-1} + \boldsymbol{\Phi}_2\tilde{\mathbf{y}}_{t-2} \dots \boldsymbol{\Phi}_p\tilde{\mathbf{y}}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{4}$$

where $\boldsymbol{\Phi}_l$ with $l = 1,2,\dots p$ are square matrices of coefficients, and $\boldsymbol{\varepsilon}_t$ is the innovation vector. We note that the model may include a large number of parameters, which may make the interpretation difficult; similarly to the NARDL case, we focus attention on a restricted parameterisation of the VAR(p) model:

$$\tilde{\mathbf{y}}_t = \boldsymbol{\Phi}_1\tilde{\mathbf{y}}_{t-1} + \boldsymbol{\Phi}_M\tilde{\mathbf{y}}_{t-1|t-4} + \boldsymbol{\Phi}_Q\tilde{\mathbf{y}}_{t-1|t-13} + \boldsymbol{\varepsilon}_t, \tag{5}$$

where $\tilde{\mathbf{y}}_{t-1|t-m} = \frac{1}{m}\sum_{j=1}^{m}\tilde{\mathbf{y}}_{t-j}$. This specification allows one to account for impacts from the previous week, from the previous month (i.e., the last four weeks) and from the previous quarter (i.e., the last thirteen weeks), mimicking the structure proposed by Corsi (2009) for modelling realised variance sequences, the heterogeneous auto regressive (HAR) model; consequently, we name the model in (5) as the VAR-HAR model.

This specification does not consider the possible different impact that positive and negative movements in oil prices and oil production have on the dynamic of changes in rig counts. To do so, we set up an extension of the VAR-HAR model accounting for the potentially different role exerted by price increases and price decreases, as well as by signed movements of oil production. Therefore, and consistent with the univariate NARDL model previously considered, we collect the changes of the filtered rig into the vector $\tilde{\mathbf{y}}_t^R = \left[\tilde{y}_{NS,t} \quad \tilde{y}_{S,t}\right]'$ and decompose the changes of the filtered oil price and oil production according to their sign, collecting them into the vector

$$\mathbf{y}_t^C = \begin{bmatrix} \tilde{y}_{O,t} I\left(\tilde{y}_{O,t} < 0\right) \\ \tilde{y}_{O,t} I\left(\tilde{y}_{O,t} \geq 0\right) \\ \tilde{y}_{P,t} I\left(\tilde{y}_{P,t} < 0\right) \\ \tilde{y}_{P,t} I\left(\tilde{y}_{P,t} \geq 0\right) \end{bmatrix} = \begin{bmatrix} \tilde{y}_{O,t}^{-} \\ \tilde{y}_{O,t}^{+} \\ \tilde{y}_{P,t}^{-} \\ \tilde{y}_{P,t}^{+} \end{bmatrix}, \tag{6}$$

where $I\left(a\right)$ is an indicator function that takes the value 1 when the condition a is true and 0 otherwise. We then combine these two vectors into $\mathbf{X}_t = \left[\tilde{\mathbf{y}}_t^{R'} \quad \mathbf{y}_t^{C'}\right]$. By using this last vector, we redefine the VAR model as follows:

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{\Phi}}_1 \mathbf{X}_{t-1} + \tilde{\mathbf{\Phi}}_M \mathbf{X}_{t-1|t-4} + \tilde{\mathbf{\Phi}}_Q \mathbf{X}_{t-1|t-13} + \boldsymbol{\varepsilon}_t, \tag{7}$$

where $\mathbf{X}_{t-1|t-m} = \frac{1}{m}\sum_{j=1}^{m}\mathbf{X}_{t-j}$ and the parameter matrices have dimension 4×6. This new parameterisation includes an asymmetric impact of oil price and quantity changes, since negative movements will have a potentially different impact compared to positive ones. The specification adopted is also similar to a threshold VAR, where the threshold is set at zero; it focuses on the changes of oil price and oil quantity, and it impacts only on the coefficients associated with these two variables. Further, our model is also a special case of a seemingly unrelated regression equations (SURE) model, where the explanatory variables include signed lagged components of a subset of the modeled variables. Thus, without introducing new acronyms, we refer to our specification of equation (7) as the SURE specification.

For the latter, parameter estimation is performed by resorting to ordinary least squares on an equation-by-equation basis, with standard inferential procedures. Furthermore, building on the estimated parameters, and taking advantage of the VAR-like structure of our model, we also proceed to the construction of the IRFs. Note that the variable ordering in the SURE model assumes that, when decomposing the innovations' covariance by means of the Cholesky approach, shocks to the conventional rigs could impact on the shale rigs, and shocks to the oil price and oil production could impact on both rig counts time series; the variable ordering we consider is thus: oil price returns; oil production returns; changes in conventional rigs; changes in shale rigs. Of course, different orderings of variables may be adopted. However, given the purpose of our paper, which is to evaluate the asymmetric impact of oil price and oil production on the shale and conventional rig movements, we investigate the possibility that oil price and production shocks impact on rig counts. The chosen ordering is coherent with such a purpose.

When computing the IRF, the different impacts of positive versus negative shocks on the oil price must be taken into account. Therefore, the IRF cannot be computed using the standard approach adopted for VAR models and must instead be based on specific recursions. Let us denote by Σ the variance-covariance matrix of $\boldsymbol{\varepsilon}_t$, with $\mathbf{L}$ the Cholesky decomposition of the covariance matrix such that $\mathbf{LL}' = \Sigma$, and by $\boldsymbol{\eta}_t = \mathbf{L}^{-1}\boldsymbol{\varepsilon}_t$ the orthogonalised innovations. Let the vector $\mathbf{e}$ identify the impulse hitting the system at time 0, and $\tilde{\mathbf{y}}_0 = \mathbf{Le}$ the contemporaneous reaction of the variables of interest. Note that the shock is a 4-variate vector whose elements are all equal to zero, except one element that takes a value equal to 1 or –1, corresponding to a positive or negative shock. Given $\tilde{\mathbf{y}}_0$, the construction of the impulse responses proceeds by iterating over the following two steps (and under the assumption that the system was in a steady state before the shock, that is, the past values of $\tilde{\mathbf{y}}_t$ were all equal to 0, and that the system receives a unique impulse at time 0):

1) given the values of $\tilde{\mathbf{y}}_t$ from time 0 to time t, calculate the components of $\mathbf{X}_t$, $\mathbf{X}_{t|t-3}$, and $\mathbf{X}_{t|t-12}$;
2) retrieve the reaction of the system variables at time $\mathbf{y}_{t+1}$ using the recursion in equation (7).

Steps 1) and 2) are iterated until the desired horizon for the IRFs is reached, which is equal to $\tilde{\mathbf{y}}_{t+j}$ for $j = 1,2,\ldots h$. Note that, given the specific lag structure we consider, we report the IRFs for h = 52 lags, corresponding to one year. Finally, the confidence intervals for the IRFs are recovered by resorting to bootstrap approaches. In detail, we resort to a residual bootstrap:

1) generate a sequence of innovations by sampling from the model residuals;
2) generate a simulated path of the variables of interest using the estimated parameters;
3) estimate the model in the simulated series;
4) with the parameters estimated in Step 3, recompute the IRF and store them.

We iterate steps 1–4 5,000 times using sample-specific coefficients, residuals and simulated series length. We report confidence intervals computed using the cross-section of the simulated IRF. In addition to simple IRF (i.e., $\tilde{\mathbf{y}}_{t+j}$ for $j = 1,2,\ldots h$) we also report cumulated IRFs, $\tilde{\mathbf{Y}}_{t+i} = \sum_{i=1}^{j}\tilde{\mathbf{y}}_{t+i}$ for $i = 1,2,\ldots h$, which allow the measurement of the long-term impact of an oil shock on the rig counts.

5. EMPIRICAL EVIDENCE

As mentioned in previous sections, we analyse three subsamples. These are defined coherently with the presence of a break in the series and separated by certain observations to improve the parameter estimation, excluding periods characterised by transition through interdependence phases. The periods are defined as follows: the first period covers up to 26th of September 2014; the second period starts from 9th January 2015 and goes up to 27th December 2019; the third period starts on 3rd April 2020 and goes until the end of the sample. On the one hand, the first and second subsamples end before the drop in oil price due to the oil glut and the pandemic. On the other hand, the periods between the first and second samples, and between the second and third samples, are not completely excluded from the analysis, as they will be incorporated within the lags in the VAR and SURE models. This is consistent with the interest in detecting the relation between rig counts and oil prices, since rig counts tend to react with some delay to oil price movements.

To evaluate the relationship between oil prices and rig counts, we first analyse the estimated coefficients of the VAR-HAR and SURE models on the two samples, which we identify by means of the analyses reported in Section 3.[12] The first sample goes from February 2011 to the end of September 2014, while the second sample starts in January 2015 and ends in December 2019. We report in Tables 5 and 6 the estimated coefficients for the first and second subsamples, respectively.

In the first period (2011–2014, Table 5), we see that only a few coefficients are statistically significant, with a slightly higher number in the case of the SURE specification. Let us start by considering oil price and production as dependent variables. In the VAR-HAR model, the oil price returns are unrelated to their lags and are negatively impacted by the previous week's oil production changes. For the SURE specification, we observe a significant impact of the negative returns observed in the last quarter; however, the impact is limited to –0.1, indicating a mild mean-reversion behavior. Looking at the oil production returns, we note that in the VAR-HAR model, weekly lagged production changes have a positive impact on current production changes with a small coefficient of 0.06. In the SURE case, the monthly and quarterly impacts are present, and are associated with negative oil production returns, with coefficients of equal size but opposite sign. For both models, neither oil price returns nor production changes are influenced by shale or conventional rig changes with a significant impact. Consider now the rig changes as dependent variables. For both the VAR-HAR and SURE specifications, the changes to the conventional rig counts seem to be characterised by a short-term mean reversion, as the one-week lag is statistically significant and negative, with a coefficient equal to –0.15, while the shale rigs show evidence of mild quarterly persistence, with a coefficient around 0.08; in absolute terms, the role of the lagged values is limited.

Let us now focus on the impact of oil price and oil production changes on rig count changes. In the VAR-HAR case, the shale rig count reacted quickly to a change in oil price. A 1% increase in oil price during the previous week leads to a decrease of 0.4 in the shale rig count differences, while conventional oil rigs do not react to price changes. Such a result can be explained by noting that the oil prices were mostly falling during the first observation period, thus, a negative change in oil price drop (i.e., an increase in absolute value) would determine a rise in the shale rig count. The SURE model partially confirms this finding. Shale rig changes react only to negative changes in oil prices, yet with a negative sign, showing that when oil price reduction decreased (i.e., less reduction), the shale rig changes rose. However, note that such an interpretation warrants some caveats: first, the relationship is only mildly significant (10% significance level). Moreover, both models include a limited R-squared in all the single equations of the model (see the last line of the table's panel), which denotes, for the rig count changes, that the activation of rigs is not necessarily associated with a movement in the oil price (and this is consistent with the limited number of statistically significant coefficients). Finally, we see a moderate positive reaction of the changes in the conventional rig counts to the changes of oil production, which occurs only due to positive changes, yet this is significant only at the 5% confidence interval.

In the second sample, as reported in Table 6, we observe a greater interdependence among the variables. The oil price returns are affected only by their own lagged effects, only accruing from positive changes (as shown by the SURE model). The significance of the weekly lagged shale rig changes is coupled with an almost null coefficient. The same can be said for oil production changes, which are influenced only by their own lagged values when they are negative and there is an irrelevant impact of shale rig changes. In both cases, the series exhibits a return to the mean behavior.

Looking at the rig count changes as the dependent variables, we first note a sensible increase in the R-squared. For both models, the conventional rig changes show a limited reaction

12. Estimated coefficients from the regression of observed series on control variables based on equation (3) are not reported here but are available from the authors upon request.

Table 5: Estimated coefficients of the VAR-HAR (columns 2 to 5) and TVAR-HAR (columns 6 to 9) models in the first sample, 2011–2014.

	VAR-HAR				TVAR-HAR			
Dependent	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$
$\tilde{y}_{Co,t-1}$	**-0.150***	<0.001	<0.001	<0.001	**-0.153***	0.007	-0.153	-0.153
$\tilde{y}_{S,t-1}$	-0.026	-0.080	-0.153	-0.153	-0.023	-0.082	-0.153	-0.153
$\tilde{y}_{O,t-1}$	10.881	**-39.689***	-0.110	**0.063***				
$\tilde{y}^-_{O,t-1}$					4.078	**-74.971***	-0.082	0.021
$\tilde{y}^+_{O,t-1}$					28.903	0.786	-0.150	0.122
$\tilde{y}_{P,t-1}$	-32.744	18.396	**-0.378****	-0.064				
$\tilde{y}^-_{P,t-1}$					-29.735	46.598	0.166	-0.188
$\tilde{y}^+_{P,t-1}$					-41.979	7.616	**-0.727*****	-0.091
$\tilde{y}_{Co,t-1\|t-4}$	0.033	-0.048	< 0.001	< 0.001	0.033	-0.047	< 0.001	< 0.001
$\tilde{y}_{S,t-1\|t-4}$	-0.019	-0.054	< 0.001	< 0.001	-0.018	-0.082	< 0.001	< 0.001
$\tilde{y}_{O,t-1\|t-4}$	-14.588	18.295	-0.013	-0.039				
$\tilde{y}^-_{O,t-1\|t-4}$					-1.912	9.874	-0.05	**-0.063***
$\tilde{y}^+_{O,t-1\|t-4}$					-30.442	29.153	-0.008	0.002
$\tilde{y}_{P,t-1\|t-4}$	**44.930****	-33.483	0.165	-0.149				
$\tilde{y}^-_{P,t-1\|t-4}$					43.325	-31.211	0.096	44.930*
$\tilde{y}^+_{P,t-1\|t-4}$					**52.932****	-41.818	0.070	-0.099
$\tilde{y}_{Co,t-1\|t-13}$	0.013	0.018	< 0.001	**< 0.001***	0.012	-0.005	0.001	< 0.001
$\tilde{y}_{S,t-1\|t-13}$	0.022	**0.080*****	< 0.001	< 0.001	0.020	**0.081*****	< 0.001	< 0.001
$\tilde{y}_{O,t-1\|t-13}$	1.043	2.207	-0.013	0.015				
$\tilde{y}^-_{O,t-1\|t-13}$					-3.932	-10.052	**-0.104***	**0.065****
$\tilde{y}^+_{O,t-1\|t-13}$					4.449	10.535	0.057	-0.014
$\tilde{y}_{P,t-1\|t-13}$	-23.815	27.719	-0.008	-0.068				
$\tilde{y}^-_{P,t-1\|t-13}$					-14.138	22.764	-0.112	-0.056
$\tilde{y}^+_{P,t-1\|t-13}$					-26.502	18.433	-0.057	0.012
R^2	0.071	0.164	0.076	0.117	0.077	0.189	0.134	0.251

Dependent variables are reported over columns, while explanatory variables are reported over rows. Statistically significant coefficients are marked in bold, while the level of significance is identified as follows: *** 1% significant, ** 5% significant, and * 10% significant. For each equation of the system, the table reports the corresponding R-squared.

Table 6: Estimated coefficients of the VAR-HAR (columns 2 to 5) and TVAR-HAR (columns 6 to 9) models in the second sample, 2015–2019.

	VAR-HAR				TVAR-HAR			
Dependent	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$
$\tilde{y}_{Co,t-1}$	**-0.246*****	0.010	0.001	< 0.001	**-0.243*****	0.008	0.001	< 0.001
$\tilde{y}_{S,t-1}$	**0.141****	**0.173***	**0.001***	< 0.001	**0.150****	**0.162***	**0.001****	< 0.001
$\tilde{y}_{O,t-1}$	-3.055	-9.372	0.095	0.022				
$\tilde{y}^{-}_{O,t-1}$					**-31.541***	2.469	-0.246	0.007
$\tilde{y}^{+}_{O,t-1}$					**26.006***	-24.891	**0.404*****	0.039
$\tilde{y}_{P,t-1}$	-15.717	25.490	0.130	**-0.189****				
$\tilde{y}^{-}_{P,t-1}$					**-42.863***	**85.405***	0.137	**-0.709*****
$\tilde{y}^{+}_{P,t-1}$					16.826	-34.932	0.102	0.095
$\tilde{y}_{Co,t-1\|t-4}$	0.106	**0.229*****	-0.001	< 0.001	0.086	**0.237*****	-0.001	< 0.001
$\tilde{y}_{S,t-1\|t-4}$	-0.016	0.055	< 0.001	< 0.001	-0.016	0.055	< 0.001	< 0.001
$\tilde{y}_{O,t-1\|t-4}$	1.829	-2.473	-0.040	-0.005				
$\tilde{y}^{-}_{O,t-1\|t-4}$					8.358	-7.710	0.054	0.030
$\tilde{y}^{+}_{O,t-1\|t-4}$					-0.016	-3.095	**-0.135***	-0.032
$\tilde{y}_{P,t-1\|t-4}$	9.344	0.943	-0.131	**-0.223****				
$\tilde{y}^{-}_{P,t-1\|t-4}$					22.775	-29.955	-0.189	**-0.140****
$\tilde{y}^{+}_{P,t-1\|t-4}$					16.285	-4.216	-0.159	-0.064
$\tilde{y}_{Co,t-1\|t-13}$	**0.034***	-0.011	< 0.001	< 0.001	**0.042***	-0.006	< 0.001	< **0.001****
$\tilde{y}_{S,t-1\|t-13}$	-0.005	0.011	< 0.001	< **0.001****	-0.007	0.010	< 0.001	< **0.001*****
$\tilde{y}_{O,t-1\|t-13}$	**4.866****	**11.302*****	0.006	0.005				
$\tilde{y}^{-}_{O,t-1\|t-13}$					**7.437***	7.522	-0.043	-0.013
$\tilde{y}^{+}_{O,t-1\|t-13}$					1.625	**18.633*****	**0.072***	0.010
$\tilde{y}_{P,t-1\|t-13}$	-2.030	9.418	0.063	< 0.001				
$\tilde{y}^{-}_{P,t-1\|t-13}$					1.430	13.180	0.090	0.039
$\tilde{y}^{+}_{P,t-1\|t-13}$					-11.366	17.324	0.187	**0.052***
R^2	0.351	0.598	0.040	0.169	0.366	0.602	0.071	0.308

Dependent variables are reported over columns, while explanatory variables are reported over rows. Statistically significant coefficients are marked in bold, while the level of significance is identified as follows: *** 1% significant, ** 5% significant, and * 10% significant. For each equation of the system, the table reports the corresponding R-squared.

to the previous week shale and the previous week and quarter own changes. The changes in the shale rig count react to those in the previous week and to the changes in the conventional rig count in the previous month. Focusing on the role exerted by oil price movements on the change in rigs, for the VAR-HAR model, we note that the previous quarter's rate of change in oil price impacts both conventional and shale rig count variations. The impact is much greater for the shale rigs: 11.3 compared to 4.9 for the conventional rigs. In other words, a 1% increase in oil price returns implies 0.1 more shale oil rigs and just 0.04 more conventional rigs.

The SURE model provides richer evidence about the interdependence of variables. The quarterly lagged oil price returns no longer explain the conventional rig count changes (the negative one is significant only at the 10% level), while a quicker time reaction emerges. Conventional rig count changes respond to the negative and positive oil price changes of the previous week, with a negative sign for the first and a positive sign for the second. This may be explained given the stability of the conventional rig count time series in the second subsample, which seems to show a high return to the mean behavior, at a very limited level. In contrast, shale oil rig changes react to the positive oil price return variation with a quarter's delay. A 5% increase in oil price returns increases the weekly variation of shale rigs by about one unit.

Finally, turning to the COVID-19 period (see Table 7), we again note that the SURE model provides a richer view compared to the VAR-HAR specification. This is evident in the oil return estimates. The SURE model has an R-squared more than double that of the VAR-HAR case, thanks to a much stronger and relevant impact of positive versus negative weekly, monthly and quarterly oil price returns. Oil production and rigs have a negligible impact on oil price returns. For oil production, both the VAR-HAR and the SURE specifications show that only past oil production changes are relevant and that the weekly and monthly impact emerge only when we condition on their sign. Moving to the conventional rig count changes, we note that in the VAR-HAR only the quarterly oil price changes have a significant and positive impact. When conditioning on oil price returns sign, the quarterly impact disappears, and a stronger weekly impact associated with oil price decreases emerges. For the shale rig counts, we have a similar and even stronger effect, given that a 2% price decrease in one week leads to a unit decrease in the shale rigs. Moreover, also a monthly effect is also present, again focused on decreases in the oil prices. The SURE model also shows evidence of an impact coming from oil production. Finally, we note that the R-squared is now extremely high, reaching 0.82 for the SURE specification.

The dynamic interdependence across all variables at all lags included in the SURE specification can be analysed through the IRF, computed following the procedure previously described. This allows us to show the asymmetric responses of conventional and shale oil rigs to shocks that hit the oil price. More precisely, the IRFs are distinguished according to the sign of shocks hitting the oil price returns. We report the response of the shale and conventional rig changes for the three samples.

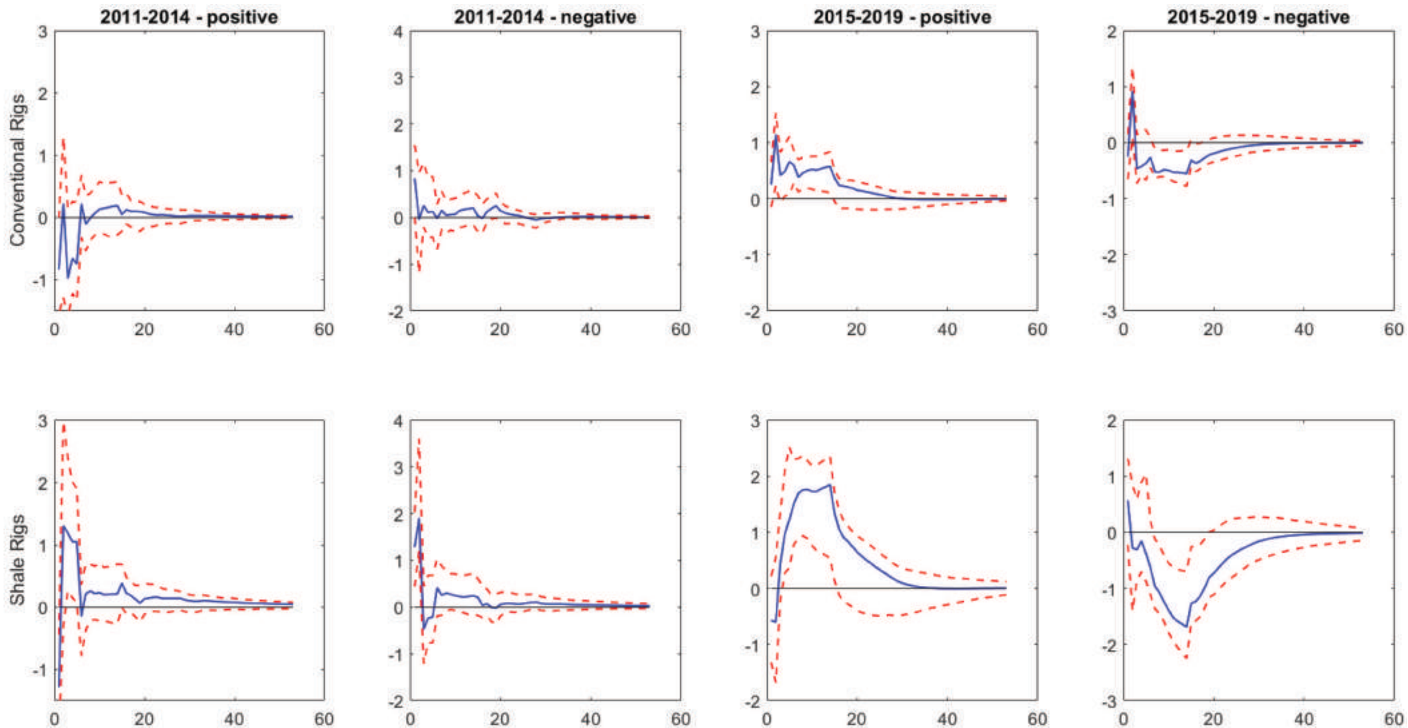
Looking at Figures 5 and 6, note that all the reported IRFs are characterised by a convergent behavior, as expected in a stable model with stationary variables: the impulse impact tends to vanish over time. We further note that, after a shock to the oil price, a significant behavior response is present for both the conventional and shale rig counts during the second sample. In the first subperiod, hardly any significant response is seen from both conventional and shale oil rigs to an impulse (either positive or negative) on the oil price returns. Looking at the second subperiod, for conventional oil rigs, we see a very limited, slightly significant and moderate response to positive price changes. Conventional rig count first rises (after a week), then reduces over time to half its value for roughly eight weeks, and then returns to the long-run mean value. Even if the moderate

Table 7: Estimated coefficients of the VAR-HAR (columns 2 to 5) and TVAR-HAR (columns 6 to 9) models in the third sample, 2020–2021.

	VAR-HAR				TVAR-HAR			
Dependent	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$	Conventional rigs $\tilde{y}_{Co,t}$	Shale rigs $\tilde{y}_{S,t}$	Price $\tilde{y}_{O,t}$	Production $\tilde{y}_{P,t}$
$\tilde{y}_{Co,t-1}$	-0.014	0.045	**0.006***	0.001	-0.087	-0.165	0.003	0
$\tilde{y}_{S,t-1}$	**0.197****	**0.564****	0.006	< 0.001	0.055	**0.174***	0.003	-0.001
$\tilde{y}_{O,t-1}$	-3.758	4.833	-0.005	-0.044				
$\tilde{y}^{-}_{O,t-1}$					**13.379***	**55.705*****	**0.813****	-0.021
$\tilde{y}^{+}_{O,t-1}$					-8.419	-10.494	**-0.462****	-0.033
$\tilde{y}_{P,t-1}$	5.744	2.661	-0.105	-0.014				
$\tilde{y}^{-}_{P,t-1}$					14.246	**41.573***	-0.139	0.247
$\tilde{y}^{+}_{P,t-1}$					-12.169	**-62.836****	-0.115	**-0.391***
$\tilde{y}_{Co,t-1\|t-4}$	**-0.161***	-0.130	< 0.001	-0.001	-0.121	0.053	< 0.001	< 0.001
$\tilde{y}_{S,t-1\|t-4}$	-0.022	-0.006	**-0.002****	< 0.001	-0.015	-0.006	**-0.001****	0
$\tilde{y}_{O,t-1\|t-4}$	-1.370	3.635	**-0.182***	0.018				
$\tilde{y}^{-}_{O,t-1\|t-4}$					4.954	**16.555****	-0.029	0.039
$\tilde{y}^{+}_{O,t-1\|t-4}$					-7.202	-10.545	**-0.438****	-0.033
$\tilde{y}_{P,t-1\|t-4}$	-12.583	9.806	-0.093	-0.098				
$\tilde{y}^{-}_{P,t-1\|t-4}$					**-19.630***	-17.841	-0.210	**-0.264****
$\tilde{y}^{+}_{P,t-1\|t-4}$					1.087	29.951	0.477	-0.067
$\tilde{y}_{Co,t-1\|t-13}$	-0.101	**0.277*****	-0.004	**0.001***	**-0.178****	0.051	-0.002	0.001
$\tilde{y}_{S,t-1\|t-13}$	0.012	-0.012	< 0.001	< 0.001	0.006	-0.028	**0.001*****	< 0.001
$\tilde{y}_{O,t-1\|t-13}$	**2.173***	**7.218****	-0.031	-0.004				
$\tilde{y}^{-}_{O,t-1\|t-13}$					-0.467	1.724	**-0.211****	-0.017
$\tilde{y}^{+}_{O,t-1\|t-13}$					-2.984	-5.516	0.007	0.001
$\tilde{y}_{P,t-1\|t-13}$	-11.825	-3.012	0.147	**-0.201*****				
$\tilde{y}^{-}_{P,t-1\|t-13}$					-9.154	-4.916	0.306	**-0.213****
$\tilde{y}^{+}_{P,t-1\|t-13}$					-7.456	**23.755***	-0.018	-0.141
R^2	0.224	0.656	0.205	0.162	0.306	0.821	0.438	0.248

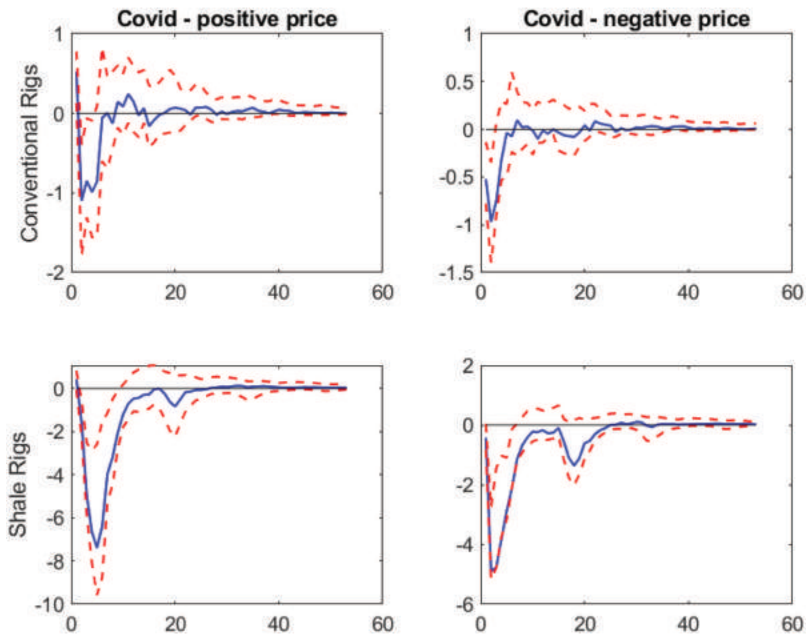
Dependent variables are reported over columns, while explanatory variables are reported over rows. Statistically significant coefficients are marked in bold, while the level of significance is identified as follows: *** 1% significant, ** 5% significant, and * 10% significant. For each equation of the system, the table reports the corresponding R-squared.

Figure 5: IRFs for the conventional rig count difference (first row) and shale rig count difference (second row) with respect to a shock on the oil price return.



Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock to the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock to the oil price returns. Confidence intervals (80% coverage) for the IRFs are obtained using a bootstrap approach adopting 5,000 replications.

Figure 6: IRFs of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to a shock on the oil price return (columns 1 and 2) or oil production return (columns 3 and 4) during the third sample (the Covid-19 period).



Columns 1 and 3 (2 and 4) refer to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRFs are obtained using a bootstrap approach adopting 5,000 replications.

reaction of conventional oil rigs is more immediate than that of the shale rigs, the latter respond more widely and for a longer period. In particular, the shale oil rigs' response to a positive oil price impulse reaches its maximum after eight weeks (two months) and maintains this level, at around 1.75, for up to 14 weeks. Interestingly enough, the reaction of shale oil rigs is 75% higher than that of conventional oil rigs. When looking at the response after a negative oil price shock, a similar behavior appears, with a stronger response from the shale rigs compared to the conventional ones (which are also not significant). Again, the negative peak for conventional rigs (around –0.5) is reached after eight weeks, while the equivalent for the shale rigs is observed after 14 weeks (with a value of –1.6); furthermore, the effect of a negative shock is more prolonged than that of a positive shock on the oil price. Overall, the IRFs for the conventional and shale rig changes show a clear asymmetric behavior when comparing the reaction with positive versus negative oil price return shocks. In addition, and even more interestingly, the reaction of the shale rigs is stronger and more persistent than the response of the conventional rigs. The shocks on the oil production are much less interesting and do not provide evidence of a significant impact in the first and second periods (see Appendix). Despite the results for the conventional rigs seem somewhat counter-intuitive, looking at them together with the existence of breaks, they signal a changing reaction in the response to oil price changes when controlling for the market state and confounding factors. In addition, we stress that the most relevant finding is the accumulated reaction, showing, coherently with the expectations, a stronger reaction of shale rigs compared to conventional rigs.

During the Covid-19 period (Figure 6), we see a significant effect of oil price shocks on shale rigs, but no significant effect on conventional rigs. The shocks accruing from production are never significant for any type of rigs (plots are reported in the Appendix). Interestingly, the IRFs show that the number of shale rigs is reduced regardless of the sign of the shocks. Such an effect is counter-intuitive; we suspect that this may be due to some further factors that may have impacted both the shale industry and the oil prices. A natural candidate would be the pandemic itself and the different policy measures implemented worldwide and across the US over time to reduce its spread and tackle its consequences. This may have played a role in affecting industry expectations, and given the quicker reaction time of shale over conventional, it may explain why only the shale rigs are affected. A different explanation refers to the mobility of human capital and goods to which the shale industry has been reacting more quickly than the conventional one. Nevertheless, we admit that these aspects deserve further analyses.

A clearer picture of the striking difference between the reaction of conventional and shale rig counts to a shock on oil prices emerges when we look at the accumulated IRFs, reported in Figures 7 and 8. Focusing on the 2015–2019 period (the most interesting), after a 1% positive shock to the oil price returns, both conventional and shale rig counts' accumulated response stabilizes after about 30 weeks.[13] However, while the conventional rigs increase by about 9.5 units, the shale rig increase reaches a value of 26, about three times the conventional rig increase. A much stronger reaction of shale rigs is also observed in response to a negative oil price return shock. In fact, again looking at the stable value observed after about 40 weeks, we note that a 1% drop in oil prices leads to a contraction of conventional rigs by 7.8 (note, however, that the confidence interval is at the edge of significance, as it is for the IRF), while the shale rigs reduce by 23. In the first and second period, the cumulated IRFs after a positive and negative shock on the oil production show no significant responses after a shock; see the Appendix for corresponding figures. For the COVID-19 period, price shocks' cumulated IRF suggest a significant negative long-run impact for shale rigs only, a counter-intuitive reaction but coherent with the IRF, as discussed above. A similar incoherence is observed for the cumulated IRF after a production shock. Again, we stress that the ongoing effect of the pandemic is, in our opinion, highly impactful on the results and requires additional future analyses.

6. ROBUSTNESS CHECK

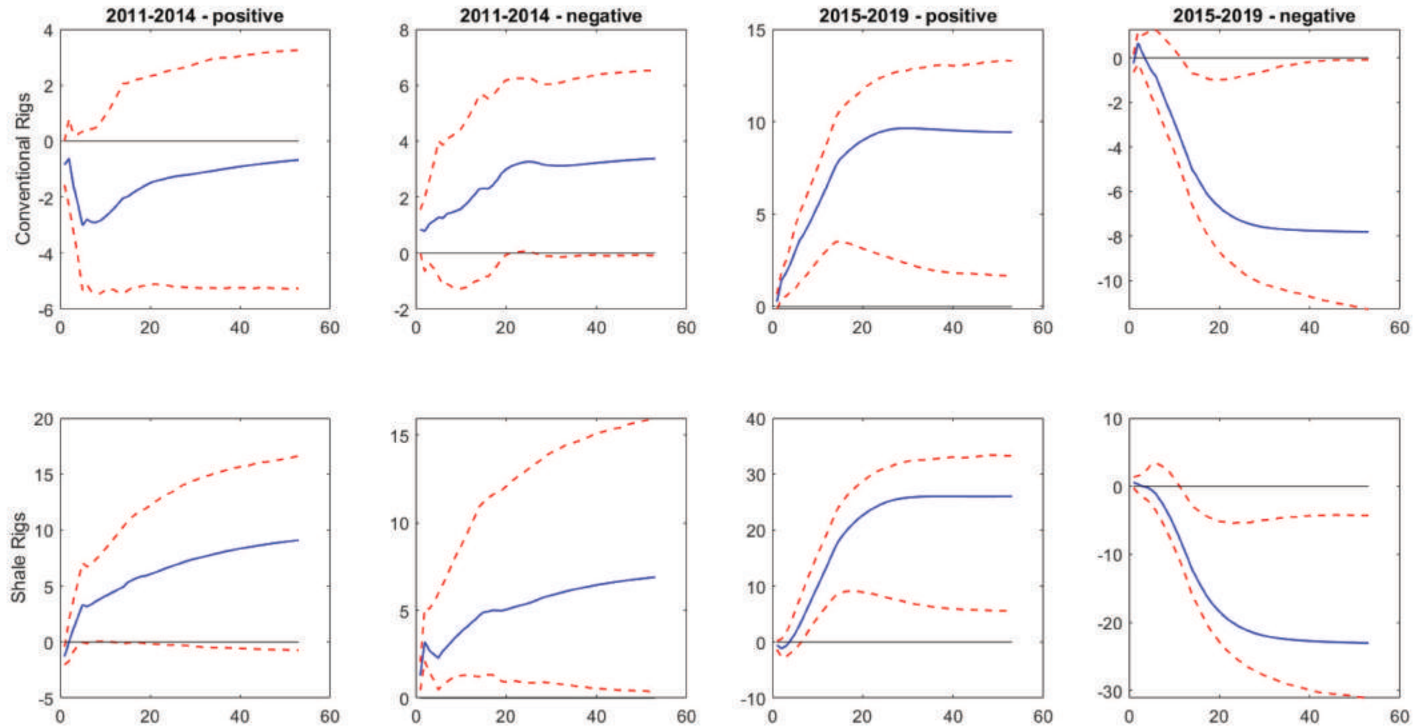
As discussed before, it has been argued in the literature that the shale rigs count—oil and gas price relationship has been influenced by the change in the number of the Developed but Uncompleted wells (DUCs). The EIA's Drilling Productivity Reports provide data on DUCs across seven shale areas: Anadarko, Appalachia, Bakken, Eagle Ford, Haynesville, Niobara, Permian.[14] Unfortunately, data of DUCs is provided on a monthly basis only. Moreover, the data does not distinguish between shale and oil DUCs. This does not allow us to use this variable as a control in our empirical analysis.[15] However, data analysis shows that from 2013 onward the overall number of DUCs has been rising up to spring 2020, where a contraction phase started. Focusing on the specific regions, and excluding from the sample the Applachian and Haynesville basins which are mostly gas areas, we see that the dynamics crucially depends on the variation in the Permian basin, while for the other four areas the number of DUCs is small, relative to Permian, and has remained substantially stable throughout the period. See Figure 9.

13. It should be noted that the IRF and cumulated IRF represent the reaction to a single impulse, while in reality, sequences of shocks are observed; this would induce a complex set of reactions that may overlap or cancel out each other depending on their signs and intensity.

14. Source: https://www.eia.gov/petroleum/drilling/

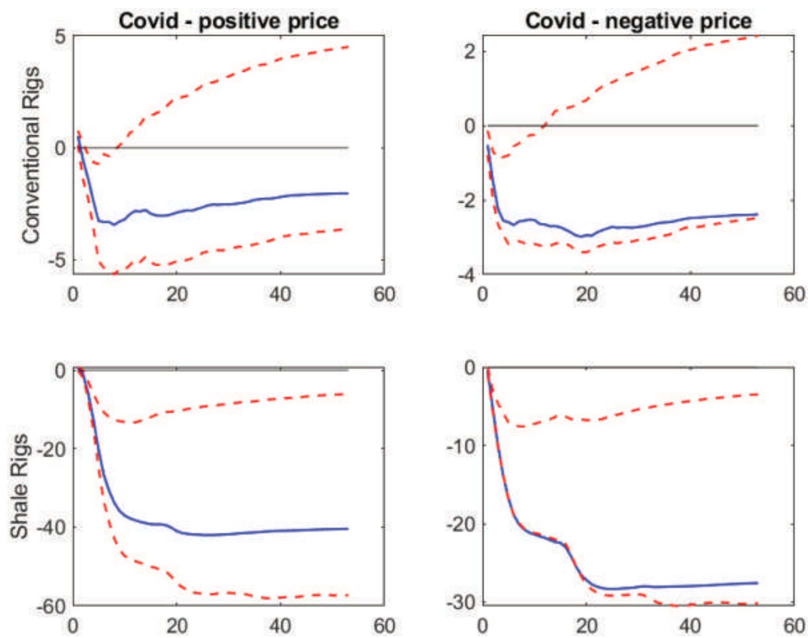
15. Our analyses are all developed at the weekly frequency.

Figure 7: Accumulated IRFs for the conventional rig count difference (first row) and shale rig count difference (second row) with respect to a shock on the oil price return.



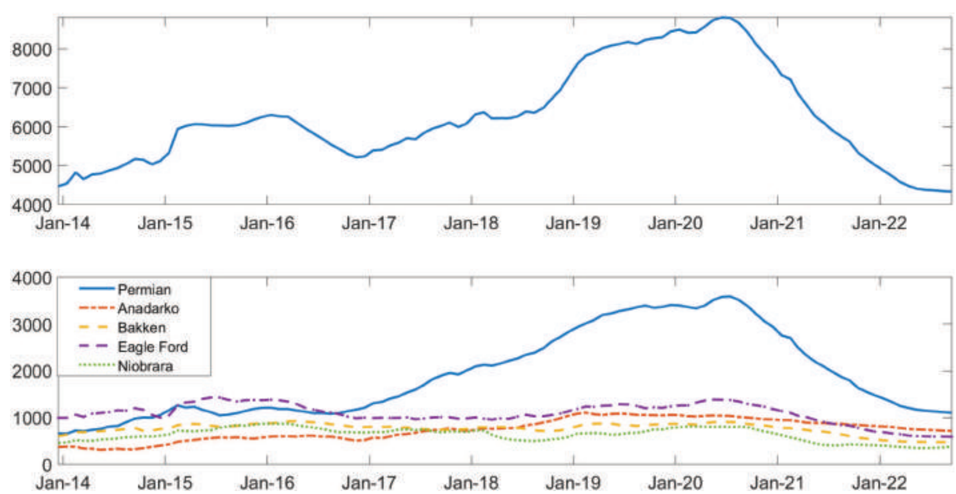
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock to the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock to the oil price returns. Confidence intervals (80% coverage) for the IRFs are obtained using a bootstrap approach adopting 5,000 replications.

Figure 8: Accumulated IRFs of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to a shock on the oil price return (columns 1 and 2) or oil production return (columns 3 and 4) during the third sample (the Covid-19 period).



Columns 1 and 3 (2 and 4) refer to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRFs are obtained using a bootstrap approach adopting 5,000 replications.

Figure 9: Drilled but Uncompleted (DUC) inventory: upper panel, total number; lower panel, specific basins.



This allows us to perform an indirect robustness test, by focusing on two sub-samples of our rig count data, namely, the Permian basin on the one hand and the remaining four areas, Anadarko, Bakken, Eagle Ford, Niobrara (ABEN), on the other.[16] They have been grouped together, given the similarity in their patterns. To determine if the DUCs have an impact on our results, we focus on model (7) and we estimate it on the Permian data as well as on the ABEN data. For the sake of brevity, we do not replicate the whole analyses, and just focus on the IRFs. The comparison of the result across regions Permian vs ABEN and with respect to the full sample will allow us to verify if DUCs, which have been changing mostly in the Permian basin, have influenced the impact that oil price has on the rig count.

Figure 10 reports the accumulated IRFs obtained by estimating the VAR model in equation (7) on the data for the Permian basin (left plots) and the ABEN basins (right plots) for the time range 2015–2019 and after a shock on oil prices. We focus on this subperiod since it is the one that provides the most interesting findings for our analyses; the complete set of plots, for other sub-periods, for both price and production shocks, and including both IRFs and accumulated IRFs, is available in the paper's Appendix. When comparing the Permian basin to ABEN basins' accumulated IRFs we first note they have very similar patterns. However, when considering the size and the significance, differences emerge. In particular, for the conventional rigs, we note that the response to price shocks is significant in the Permian basin case only, and slightly larger after a positive price shock. Differently, in the ABEN case, the response is not statistically significant. If we consider the shale rigs, both Permian and ABEN basis show significant reactions to price shocks, with comparable patterns, but with cumulated reaction larger after positive shocks for the Permian case and after negative shocks in the ABEN case. Comparing Figure 10 plots with those in Figures 7 and 8 we note that the full sample pattern are closer to the Permian ones. Nevertheless, the differences between the latter basin, which has the largest DUCs' fraction and the other ones are limited, suggesting that our results is only marginally impacted by the presence of DUCs. However, we cannot exclude that other structural factors, not included in those accounted for in our analyses, might be responsible of the observed heterogeneity.[17]

Similar evidence, showing the comparability between full sample analyses and the analyses made at the basin's level, are observed also across periods and when considering productivity shocks (see the Appendix).

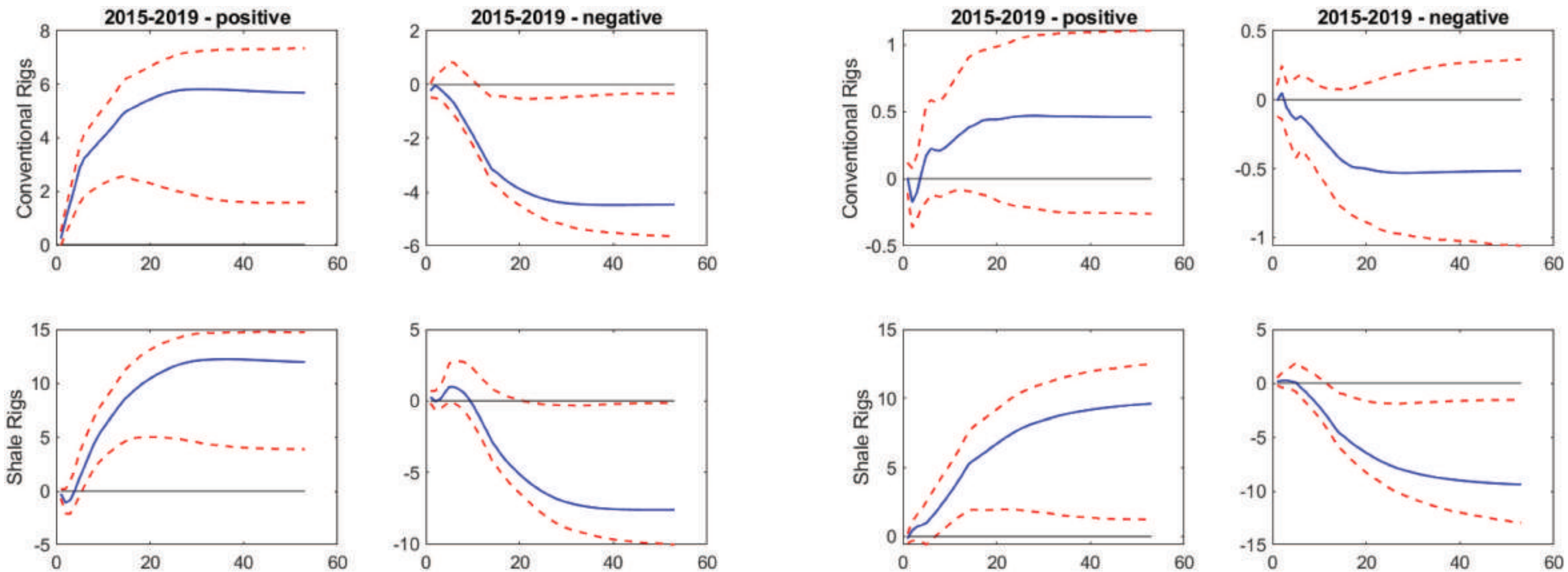
7. CONCLUSION

In this work, we have studied the relationship between shale and conventional oil rig counts in the United States and WTI prices, controlling for economic and financial confounding factors and studying both the asymmetry of the responses and the causality ordering between variables. We first showed the existence of two structural breaks in the oil price-rig count relationship for both conventional and shale rigs. The breaks divide the analysis into three subperiods, from the beginning of the series up to the major oil price drop of 2014, from the price recovery up to the outbreak of COVID-19, and from then onward. The first period is characterised by a considerable increase in shale oil supply. The rig count analysis shows that only the shale rig count responded to positive variation in the oil price returns. The second subperiod analysis shows that shale rig counts react more heavily to oil price changes, while conventional ones exhibit a more stable behavior. However, the shale counts react with a higher time delay, that is, after a quarter. The timing of this reaction can

16. As we argument before, we exclude the Applachian and Haynesville basins as they are producing mostly gas. Moreover, we exclude the other basins where we do not have data on the DUCs.

17. We stress that a detailed analysis of the structural causes that lead to the different results between the Permian and ABEN basins is beyond the scope of the present work.

Figure 10: Accumulated IRFs for the conventional rig count difference (first row) and shale rig count difference (second row) with respect to a shock on the oil price return, for the 2015–2019 sample.



Columns 1 and 2 report the IRF for the Permian basin after a unitary positive (col. 1) or negative (col. 2) structural shock to the oil price returns; columns 3 and 4 report the IRF for ABEN basins after a unitary positive (col. 3) or negative (col. 4) structural shock to the oil price returns. Confidence intervals (80% coverage) for the IRFs are obtained using a bootstrap approach adopting 5,000 replications.

be explained by considering the timing of the production activity of shale fields. After rigging, the completion phase usually takes between three to five months.[18] Finally, the evidence for the COVID period is less clear. It is confirmed that the shale rig counts react more than the conventional ones to oil price shock; however, this reaction does not depend on the sign of the price shocks. Such a behavior could be due to the existence of some heterogeneous factor, such as the COVID-related policy measures implemented, or also due to limited observation. In any case, further analysis is needed with longer time series and after the end of a pandemic, which, at the time of the completion of this article, is still ongoing.

Nevertheless, the analyses of the first two subperiods, before the outbreak of COVID-19, performed through the IRFs confirm the asymmetric response of shale and conventional oil rigs to changes in WTI prices. First, it is confirmed that the causality runs from WTI prices to changes in the number of shale and conventional oil rigs, as no impulse from any other variable has a significant impact on the number of rigs. The only significant response is the negative (positive) change in shale oil rig counts due to a fall (rise) in oil price returns, and the rise of conventional oil rigs as a consequence of a positive increase in oil price returns. For the latter, the impact is smaller and lasts shorter than for the shale rigs. The rise in shale oil rigs following an oil price return increase has a higher intensity and a more prolonged impact over time, even if this is more limited at the very beginning than in the case of conventional rigs. The impact is slightly smaller for negative oil price returns, yet it lasts longer than for positive ones. In summary, the shale industry responds to oil price returns such that, from 2015 onwards, a positive 1% WTI price increase (decrease) would induce an overall effect after 30 weeks, which increases by 25 units (reduces by 20 units) the shale rig count. The response of the conventional industry is quicker, ends up in about 20 weeks, yet it is much smaller: a positive (negative) 1% shock induces an accumulated effect of 8.8 (6.7) conventional oil rigs.

The different dynamics of rig counts in each period can depend on several factors. A natural candidate would be the oil price volatility, which has risen in the second period. Our result thus would complement the findings of Newell and Prest (2019), who estimate a 13-fold larger supply response due to shale shale activity. With regards to this study, we show that such a response is indeed asymmetric with respect to the sign of the oil price change. Other factors that might explain the different rig count response due to the structural change, before and after the oil glut, could be the change in the structure of the oil supply coupled with the drop in conventional oil production induced by the expansion of fracking activity in the second period. Such an interpretation would be coherent with the findings of Walls and Zheng (2022), who show an asymmetric response to rise and fall of oil price. In any case, regardless of the identification of the specific factors, our analysis show that structural brakes exist and play a major role in the assessment of the rig—count shale oil price relationship; neglecting them would lead to an incorrect evaluation of the statistical properties of the time series relationships and to erroneous quantitative assessments.

These findings can be of interest to the oil industry in terms of performing more accurate estimates of drilling rig counts and the need for frac counts while considering WTI prices. The financial industry could also benefit by the information about the relationship between financial and economic variables, oil price and industry reaction. More broadly, the study offers valuable insights to all those interested in identifying and quantifying the determinants of conventional and shale oil rig count changes. Finally, as pointed out in the literature section, the asymmetric rig count reaction to oil price changes between conventional and shale rigs can help to shed light on the potential of the US shale industry to cope with price variation and clarify to what extent the US shale supply has

18. See, for instance, www.ukoog.org.uk/onshore-extraction/drilling-process.

impacted OPEC's ability to influence world oil price (Walls and Zheng, 2022). About this aspect, our results help clarify the causality of the rig count—oil price relationship and quantify both the magnitude and the timing of such a relationship, information that can be of utmost importance for the whole world oil market.

ACKNOWLEDGMENTS

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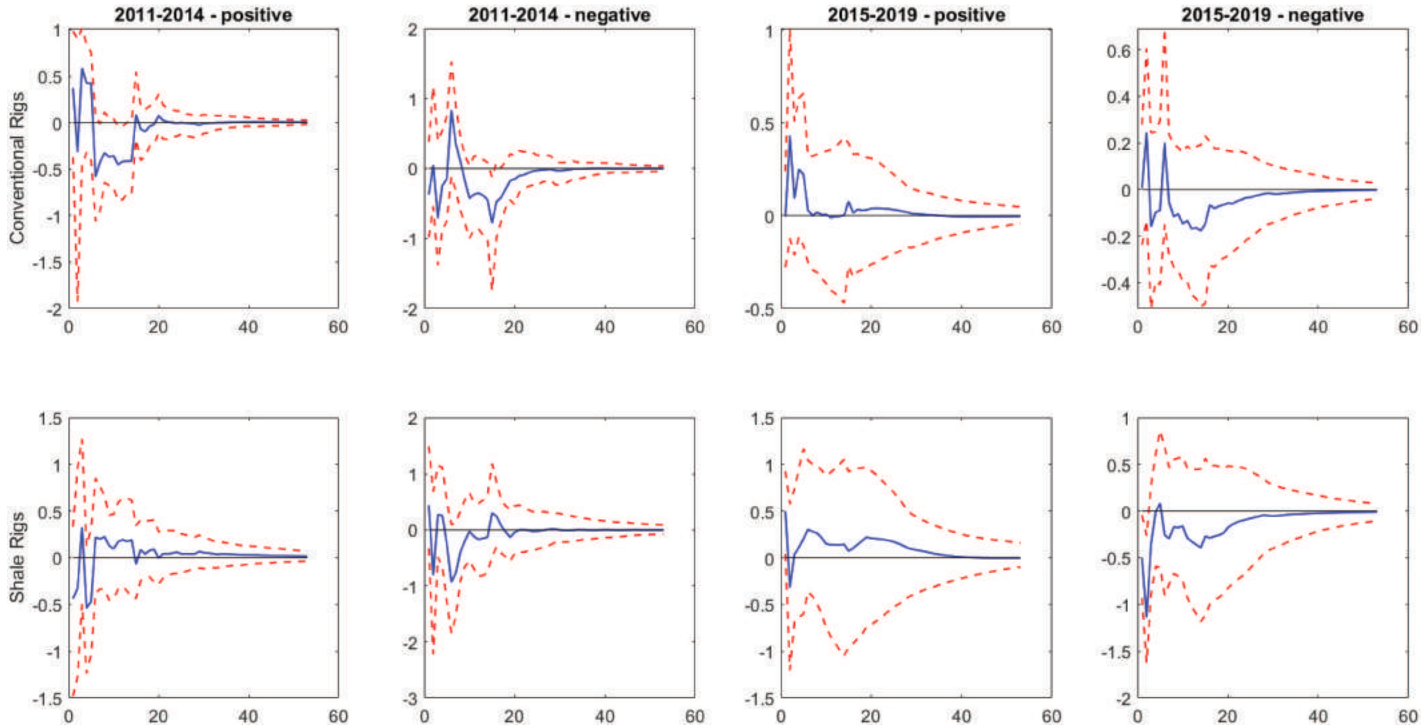
APPENDIX

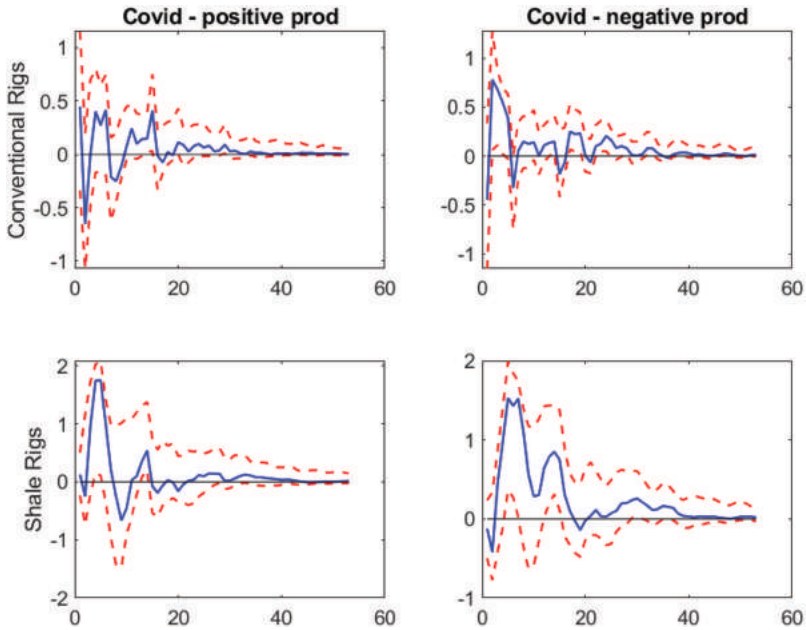
Additional Figures

Figure 11: Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



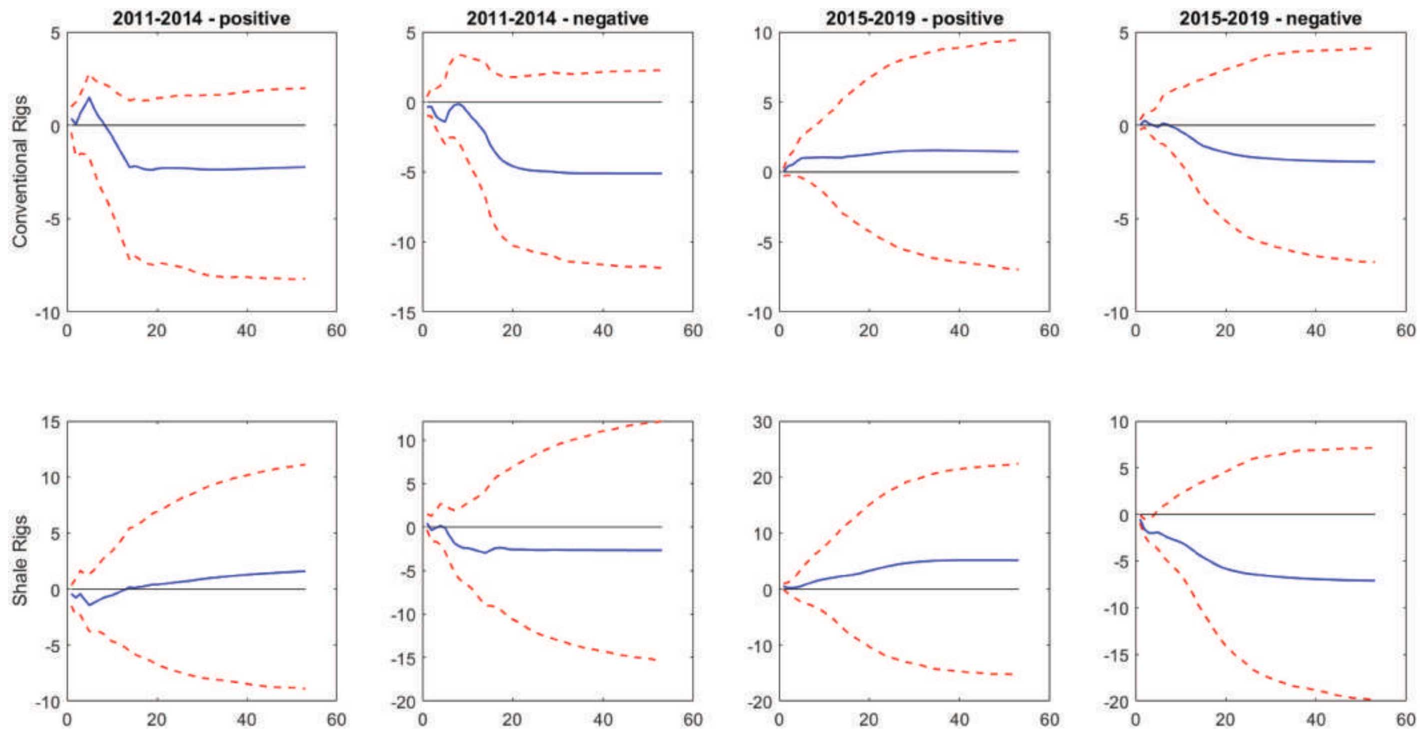
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 12: Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



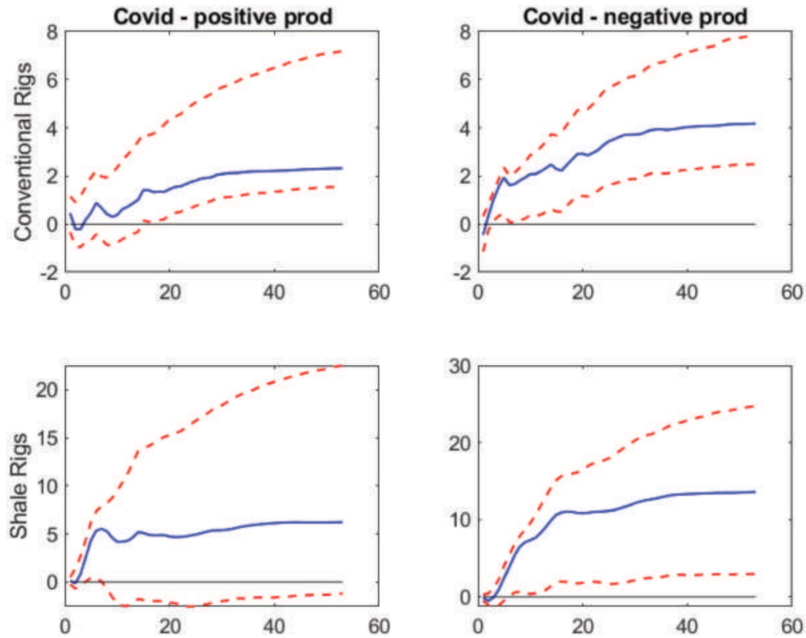
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 13: Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



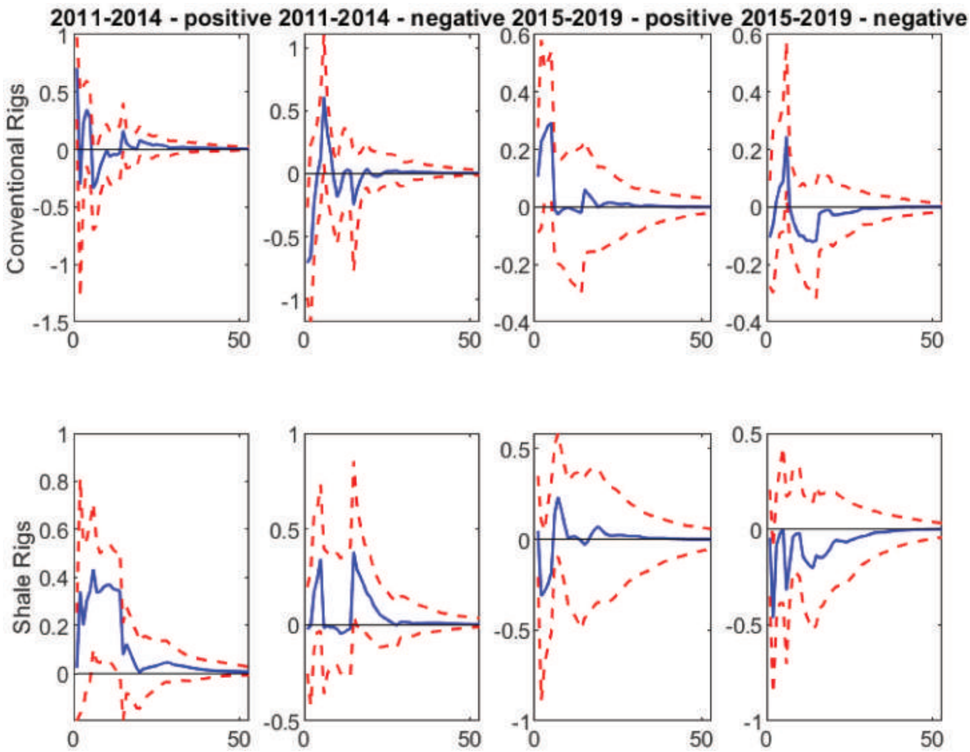
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 14: Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



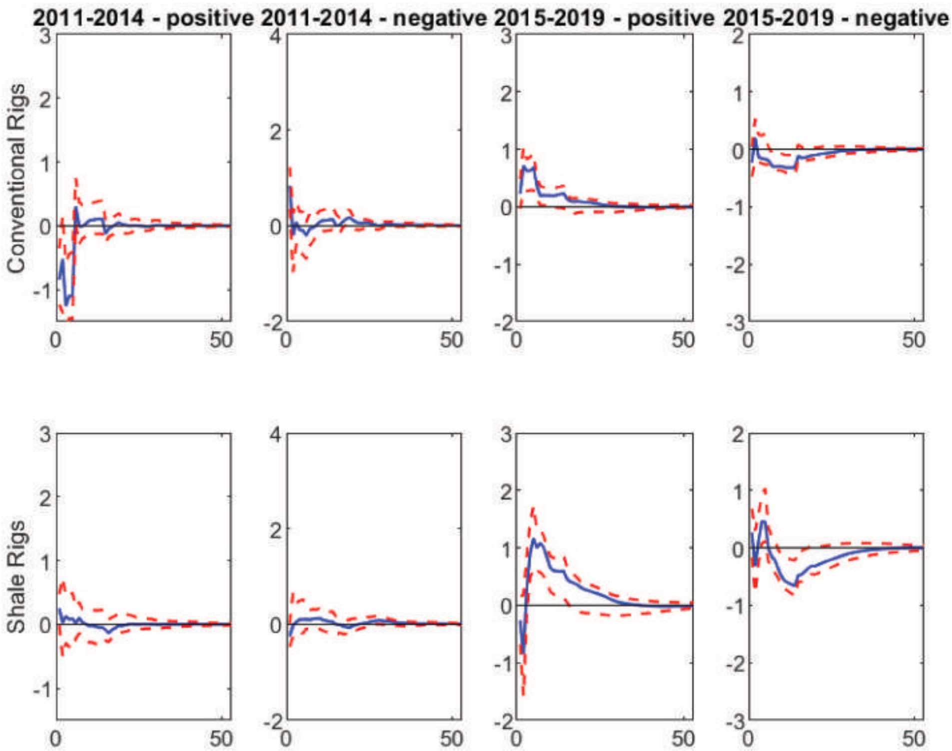
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 15: Permian basin Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



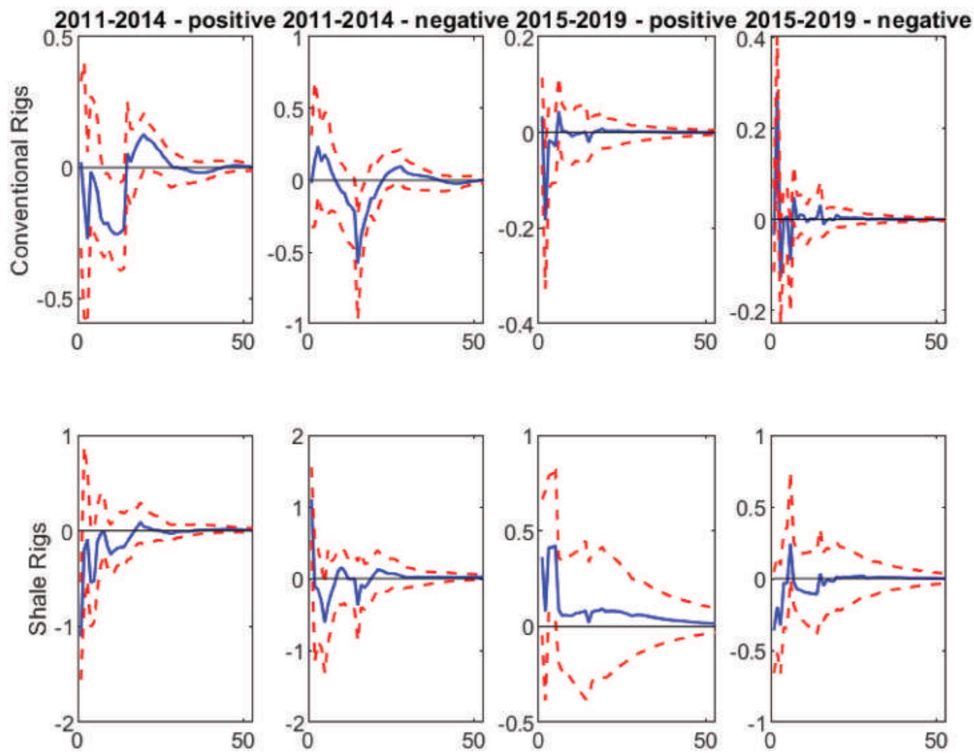
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 16: Permian basin Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return.



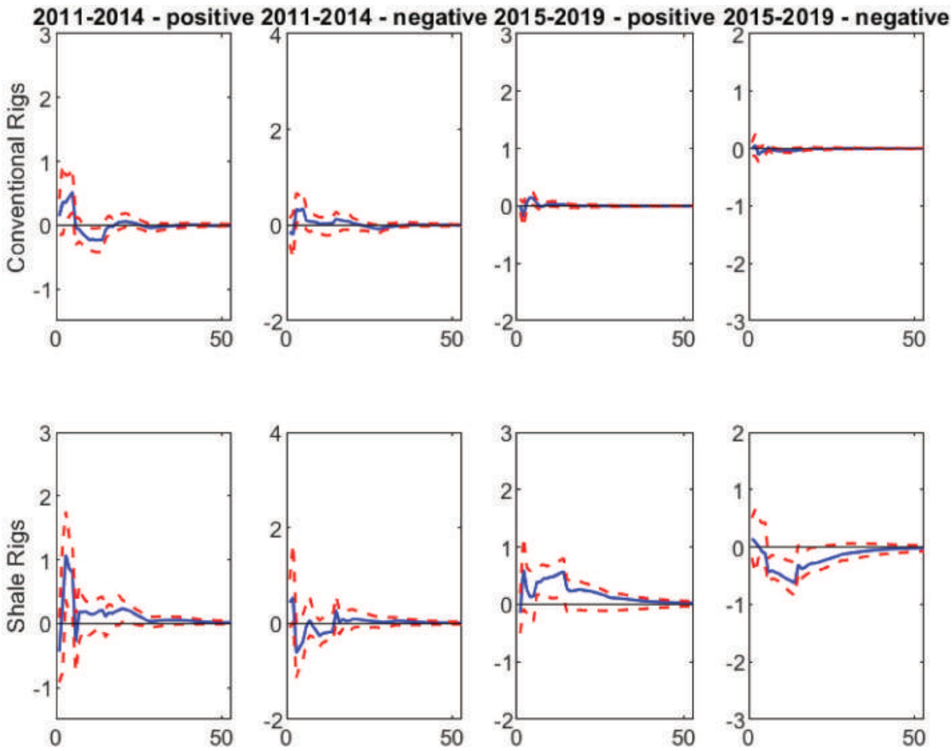
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil price returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 17: ABEN basins Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



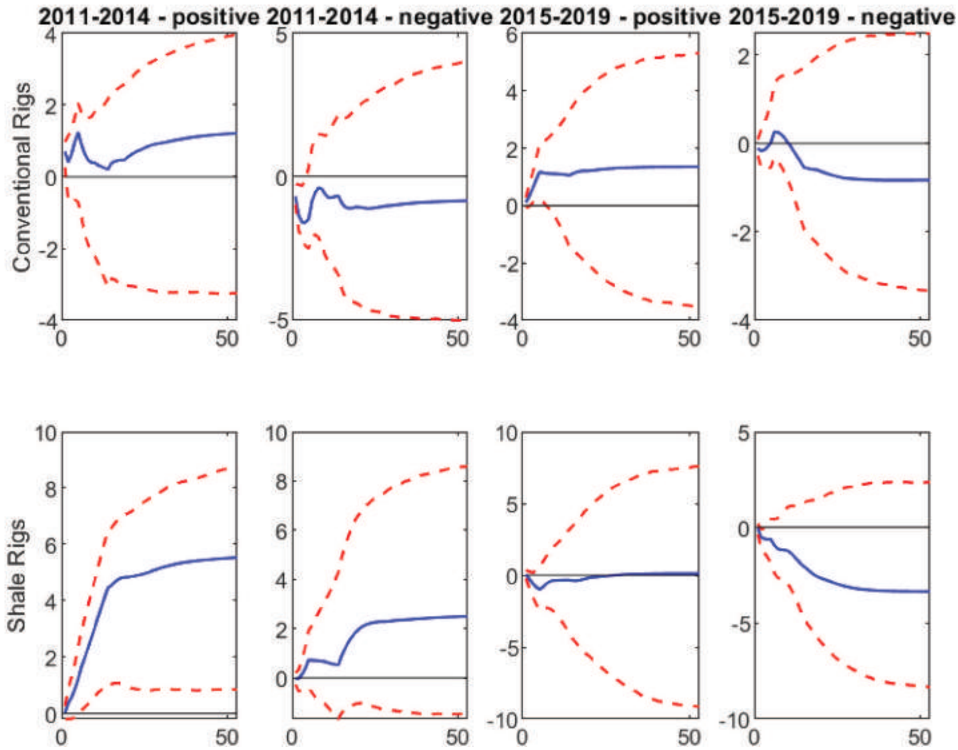
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 18: ABEN basins Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return.



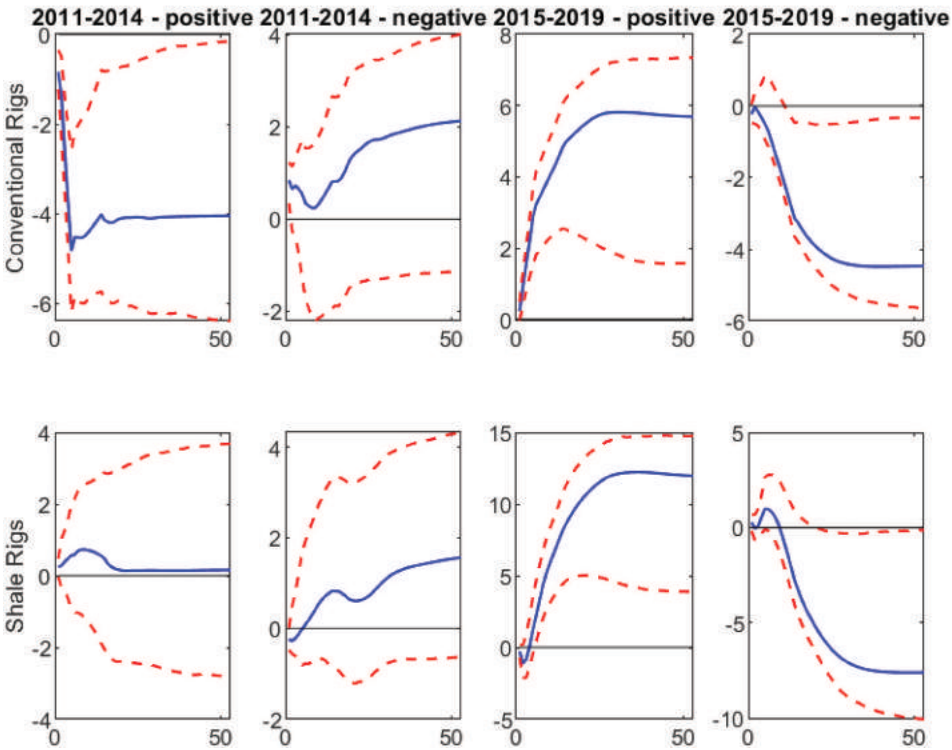
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil price returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 19: Permian basin Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



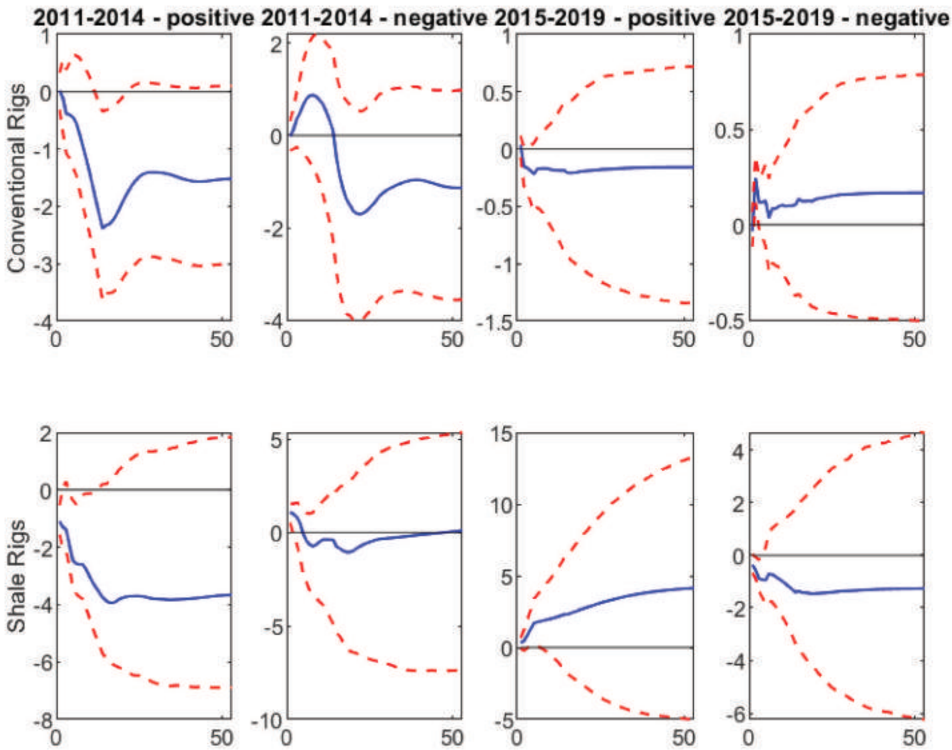
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 20: Accumulated Permian basin Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return.



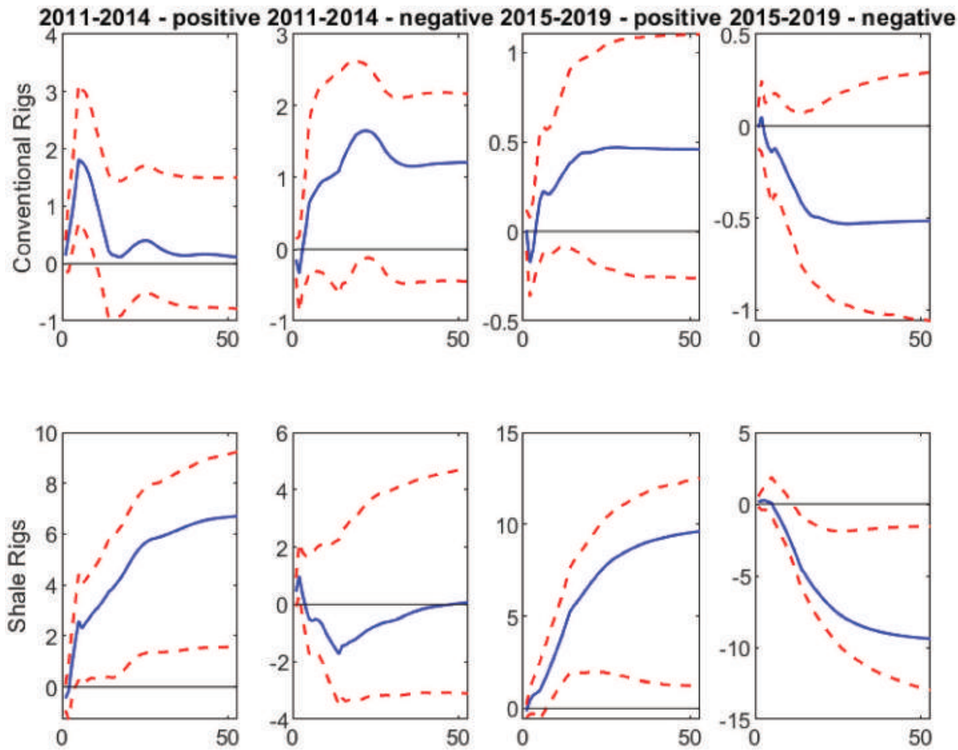
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil price returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 21: ABEN basins Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return.



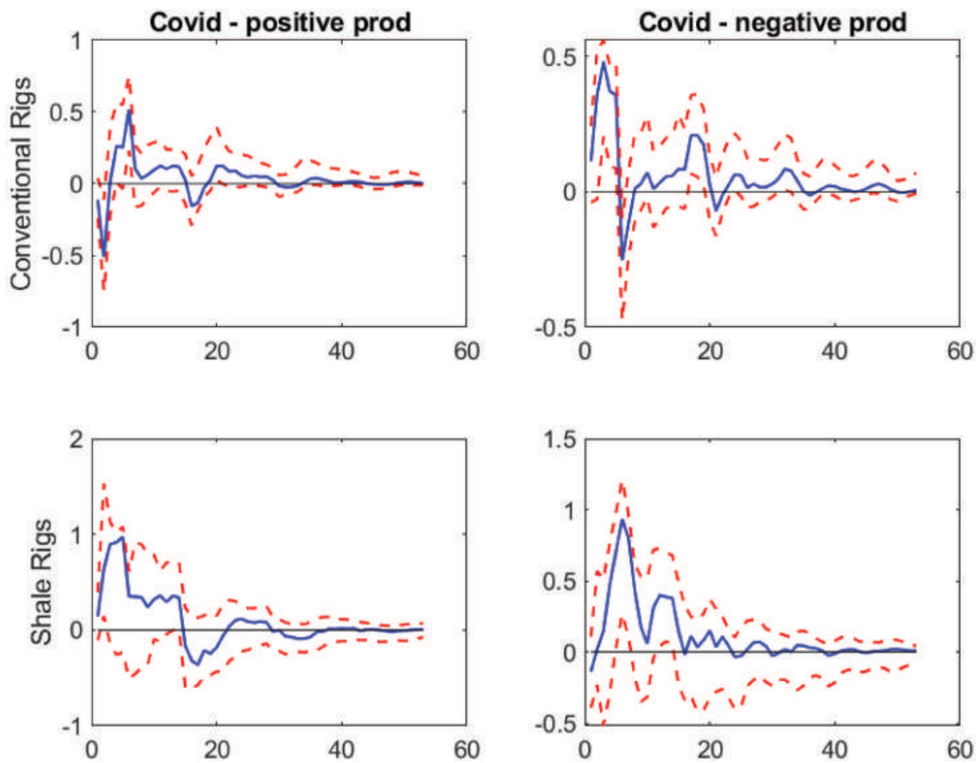
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil production returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil production returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 22: ABEN basins Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return.



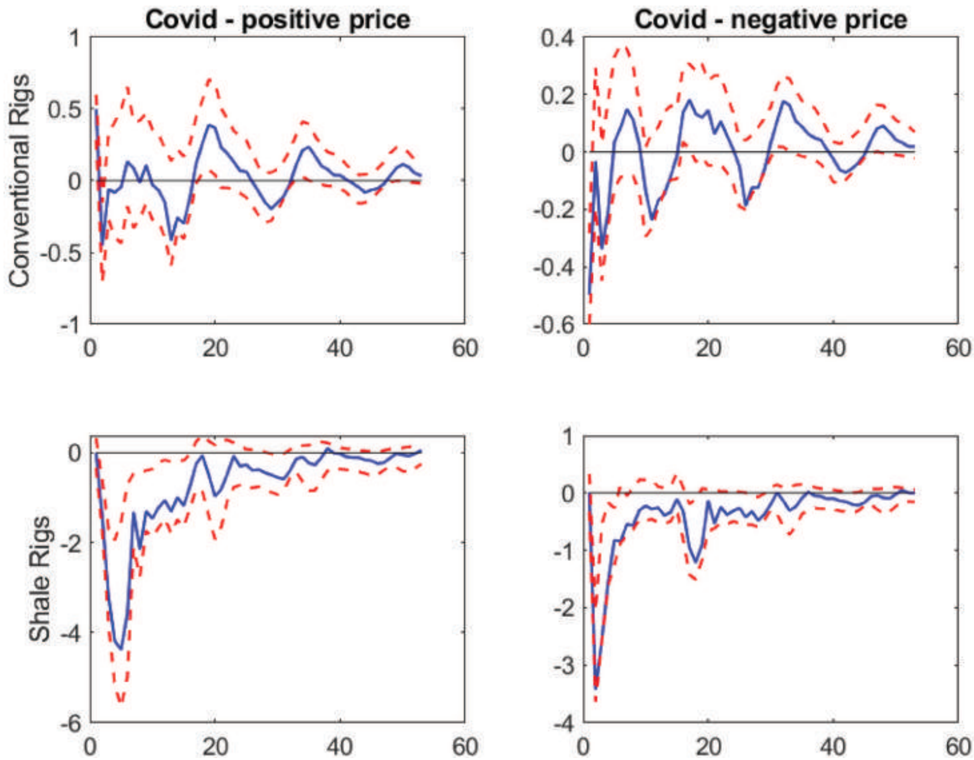
Columns 1 and 2 report the IRF for the first sample, 2011–2014, after a unitary positive (col. 1) or negative (col. 2) structural shock on the oil price returns; columns 3 and 4 report the IRF for the second sample, 2015–2019, after a unitary positive (col. 3) or negative (col. 4) structural shock on the oil price returns. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 23: Permian basin Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



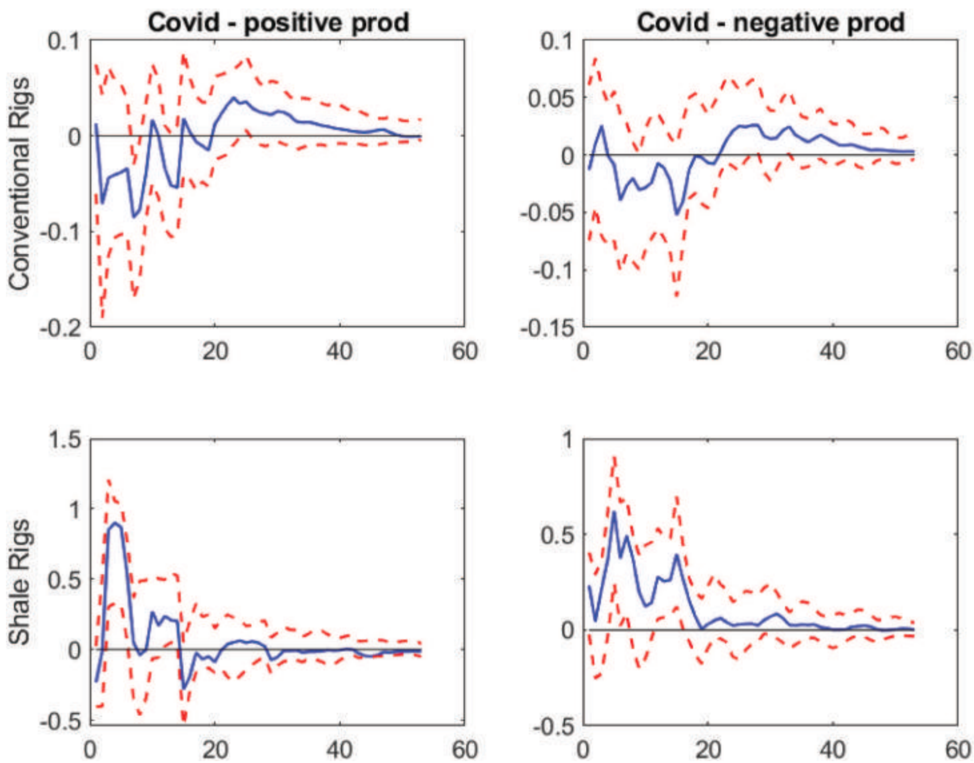
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 24: Permian basin Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return during the third sample (the Covid-19 period).



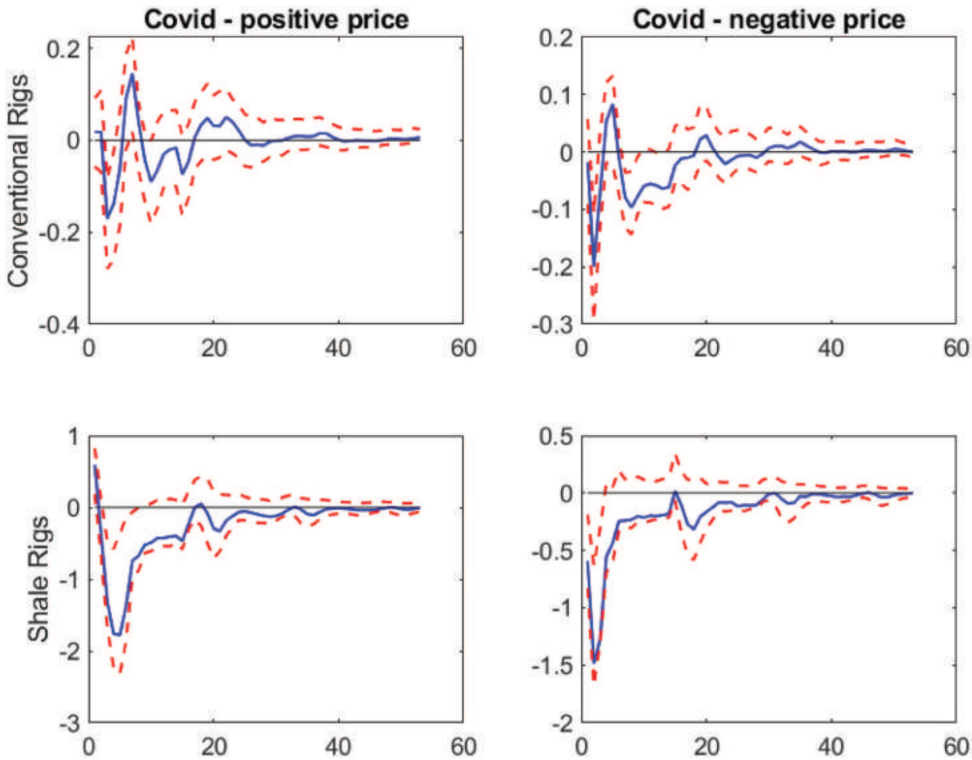
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 25: ABEN basins Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



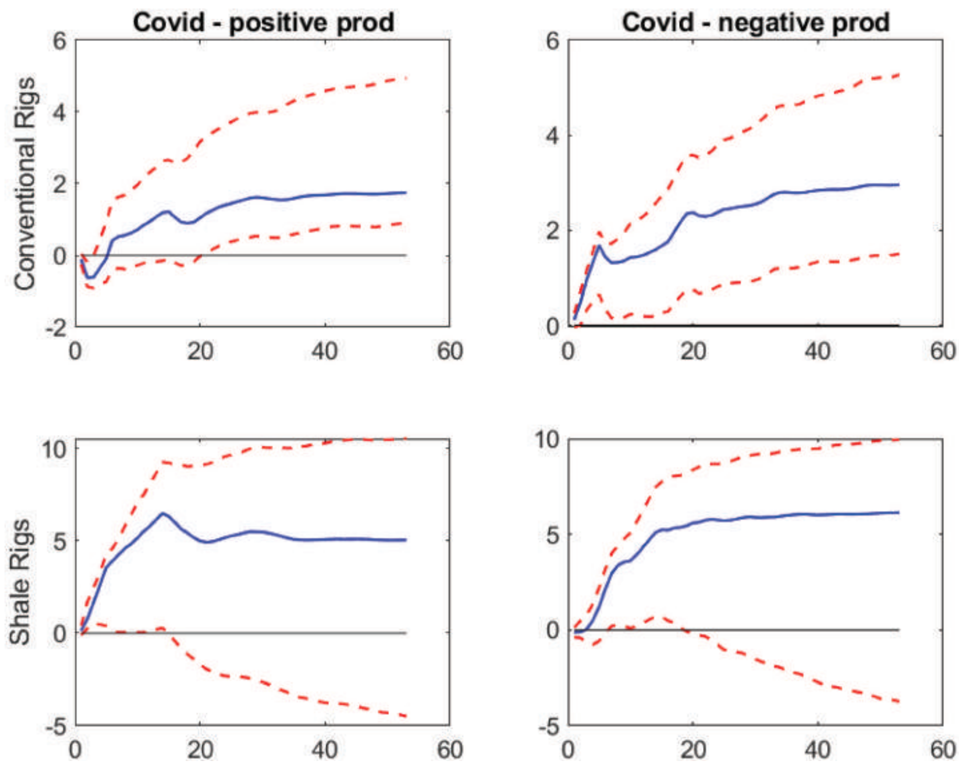
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 26: ABEN basins Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return during the third sample (the Covid-19 period).



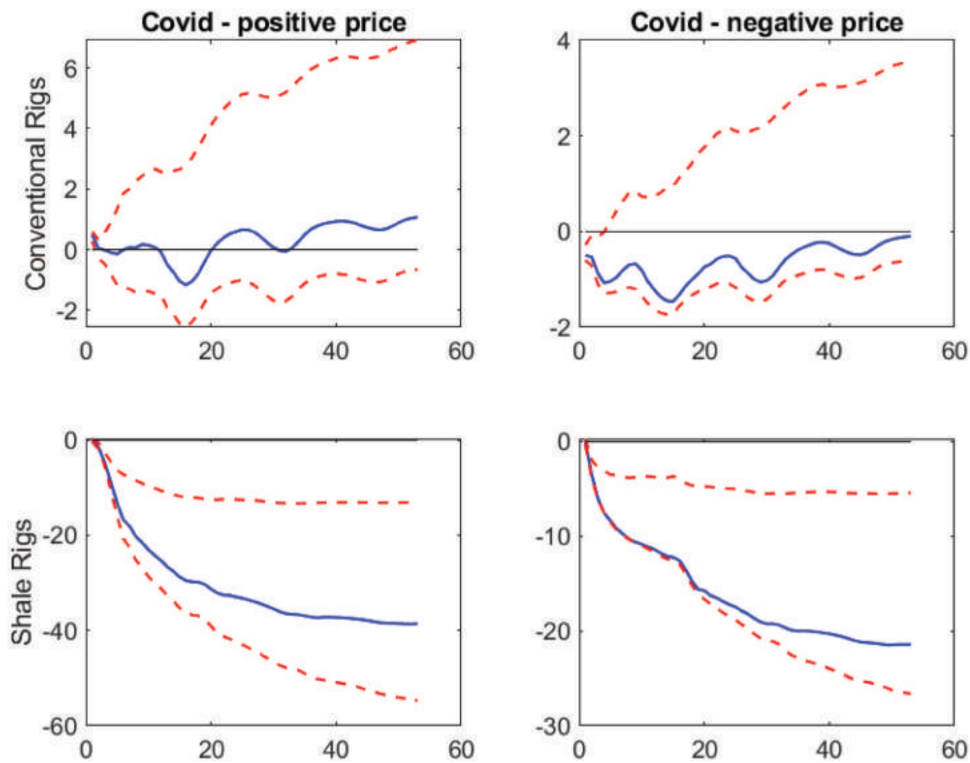
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 27: Permian basin Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



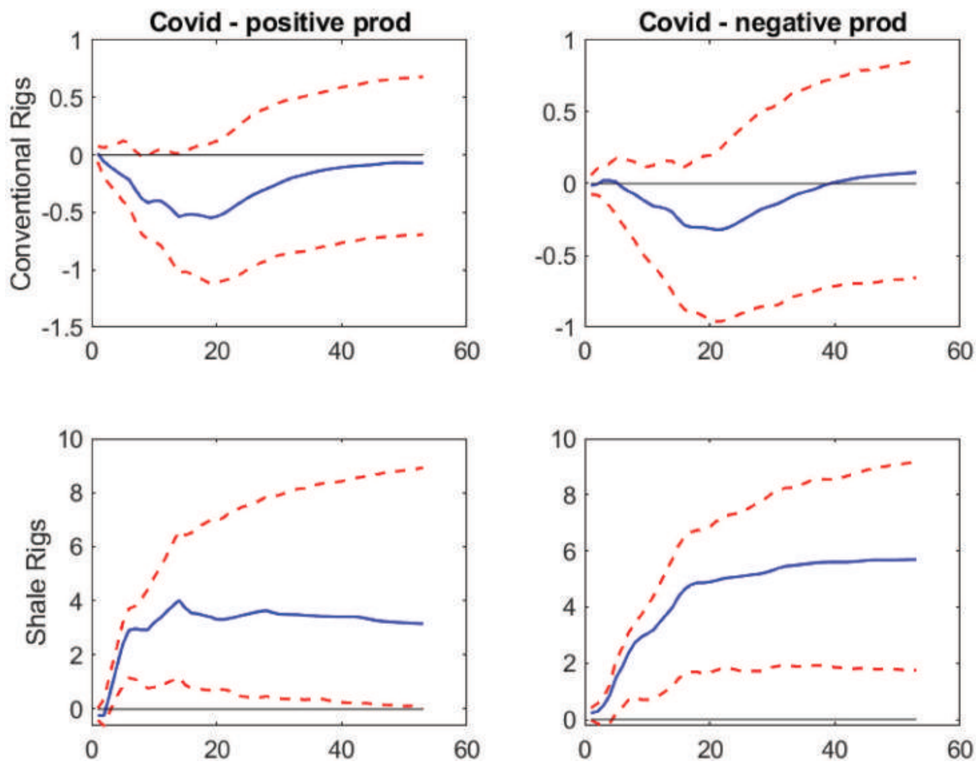
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 28: Permian basin Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return during the third sample (the Covid-19 period).



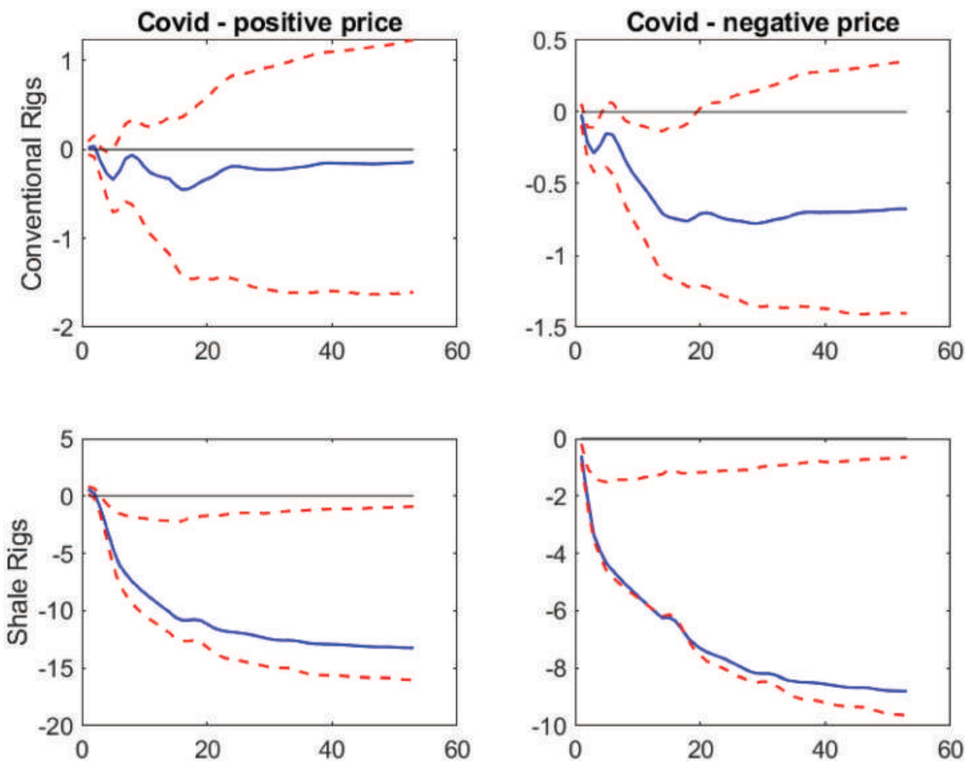
Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure 29: ABEN basins Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil production return during the third sample (the Covid-19 period).



Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

Figure30: ABEN basins Accumulated Impulse Response Functions (IRF) of the conventional rig count difference (first row) and shale rig count difference (second row) with respect to an impulse on the oil price return during the third sample (the Covid-19 period).



Column 1 (2) refers to a unitary positive (negative) structural shock. Confidence intervals (80% coverage) for the IRF are obtained with a bootstrap approach adopting 5,000 replications.

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