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RESEARCH ARTICLE

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Supply flexibility in the shale patch: Evidence from North Dakota

Hilde C. Bjørnland[1] | Frode Martin Nordvik[2] | Maximilian Rohrer[3]

[1]Department of Economics, BI Norwegian Business School, Oslo, Norway

[2]School of Economics, Innovation and Technology, Kristiania University College, Oslo, Norway

[3]Department of Finance, Norwegian School of Economics, Bergen, Norway

Correspondence
Hilde C. Bjørnland, Department of Economics, BI Norwegian Business School, Oslo, Norway.
Email: hilde.c.bjornland@bi.no

Summary

This paper provides new results to the literature, showing that output flexibility in oil production depends on the extraction technology. In particular, constructing a novel well-level monthly production dataset covering more than 16,000 crude oil wells in North Dakota, we find supply elasticity of shale wells to be positive and in the range of 0.3–0.9, depending on wells and firms characteristics. We find no such responses for conventional wells. We interpret the supply pattern of shale oil wells to be consistent with the Hotelling theory of optimal extraction. Reserves are an inventory, and the decision to produce is an intertemporal choice of when to draw down below-ground inventory.

KEYWORDS

Hotelling theory, supply elasticity, US shale oil boom, well panel data

1 | INTRODUCTION

Since the summer of 2014, the global oil industry has undergone a period of turmoil, the initial cause of which was the plunging oil price, which at one point fell more than 70% compared to the observed price level in June 2014. Since then, oil prices have remained volatile, falling abruptly again in the recent coronavirus pandemic and subsequent global crisis. For the oil industry, such volatile prices are challenging. In particular, as oil producers are typically thought to be price inelastic in the short run, they are restricted from shifting output intertemporally when prices suddenly change; see, for example, Hogan (1989), Pesaran (1990), Dahl and Yücel (1991), Ramcharran (2002), Smith (2009), Griffin and Teece (2016), and Anderson et al. (2018) for empirical evidence. Hence, oil producers are thought to do little or nothing, when prices suddenly fall.

One caveat of this conclusion, however, is the fact that it is based on studies analyzing output responses from conventional oil pools only, as the above-mentioned studies. Yet it is well known that aggregate elasticity of oil supply depends on the extraction technology of the marginal producer of crude oil. Arguably, the present marginal producers are US shale (unconventional) oil firms.[1] By 2017, oil production from shale deposits accounted for half of US crude oil output, and by 2030, 85% of the increase in global oil production is expected to come from US shale, according to IEA (2019). Furthermore, there is a potential that shale oil can spread to other oil-producing countries that have vast global unconventional shale reserves (see Clerici & Alimonti, 2015).

So while knowledge of producer behavior and supply elasticity in unconventional oil pools is important, it is lacking. We contribute to the literature by examining the response of both shale and conventional crude oil wells to spot and expected future oil prices at a monthly frequency. Constructing a novel and rich monthly panel dataset from 1990 to

[1]In the paper, we use the terms “shale” and “unconventional” interchangeably.

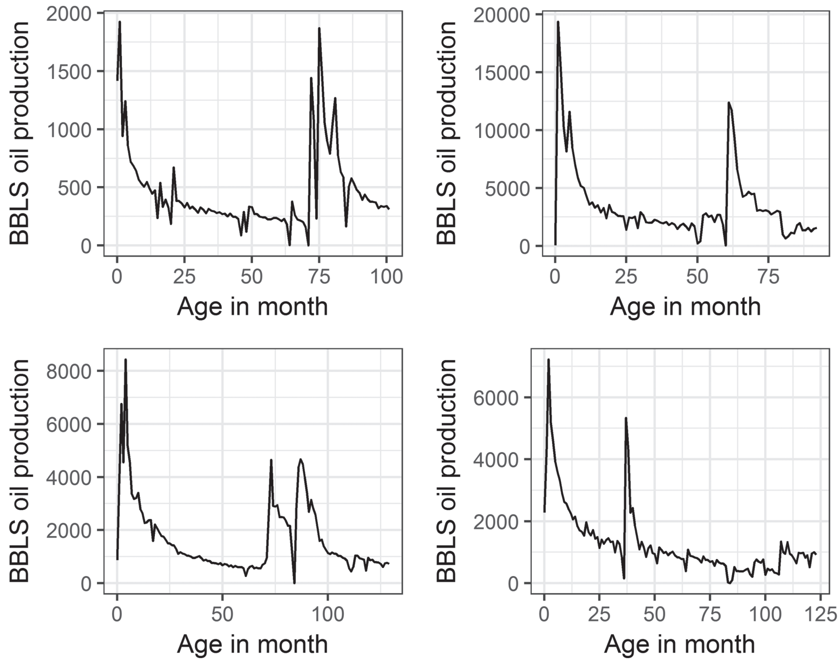


FIGURE 1 Spiky production profiles for shale wells. Note that each of the four plots shows the production profile of an unconventional well in North Dakota. Although the production amount and time differ for each of the selected individual wells, all depict clear spikes from repeated fracking

2017, covering more than 16,000 oil wells operated by more than 337 oil-producing firms, both conventional and shale, in the North Dakota oil patch, we are able to study the response of crude oil wells along two margins. First, along the *intensive* margin, we ask if firms adjust the flow rate from existing wells in response to oil price shocks, distinguishing between conventional and shale oil wells. Second, along the *extensive* margin, we ask if firms optimize the completion of new wells in response to oil price changes, comparing again the two types of well technologies. The decision to complete a well is equivalent to exercising the real option to produce, because this is the actual start of production from a well.[2] Importantly, we include both spot prices and spot-futures spreads in the estimations. US shale producers can lock in prices for their production months into the future and then sell at opportune moments. The futures market for crude oil therefore provides intertemporal price signals that producers also consider closely. In particular, if spot prices increase relative to the future, we would expect the well owners to maximize profit by increasing production today, and vice versa if the spread is decreasing.

We postulate that shale firms more often than conventional firms leave wells that are drilled uncompleted, or in below-ground storage, so as to optimize the timing of well completion. There are several reasons for this. First, shale oil wells have a much higher marginal cost per barrel, increasing the risk of prices entering the range of marginal costs inducing firms to reduce output or shut in the well temporarily. Second, shale technology is a more flexible well extraction technology, making firms less constrained in taking advantage of real option values. For example, a shale well may be stimulated with water and chemicals many times during its lifetime; see Figure 1 for empirical evidence using our dataset. This gives the well operator a certain degree of freedom to choose the timing of the fracturing operations relative to a conventional well, which is naturally flowing. Third, shale wells have a very front-loaded production profile relative to conventional wells. As we will see in more detail below, in the first 2 years of the lifetime of a shale well, production declines by a monthly rate twice as high as the average decline rate for conventional wells. As a consequence, the corresponding half-life of production is nearly twice as long for conventional wells as for shale wells. This production front-loading increases the incentive for shale producers to optimize the timing of well completion.

Using the full panel of output per well, and distinguishing between the two different well technologies, we document that (i) shale wells have a positive and significant short-term supply elasticity in response to spot price changes and to shifts in the 3-month spot-futures spread. In particular, we find the supply estimate to be significantly positive and in the range of 0.3–0.9, depending on well and firm characteristics. The largest response is found for younger wells (wells younger than 3 years) and for large firms (top 99 firms with highest production volumes). Contrastingly, conventional oil wells do not respond significantly to price changes. The latter finding is in line with what has been found in previous studies of

[2]Note that the timing of when to produce is different from the timing of the drilling of the well. The reason is that wells are frequently drilled but left uncompleted for some time. Once a well is completed, however, it starts producing.

conventional oil; see, for example, Rao (2011), Ramcharran (2002), Dahl and Yücel (1991), Jones (1990), Hogan (1989), and Griffin (1985). Furthermore, (ii) shale firms also respond to prices when deciding when to put new wells on stream. For a 10% increase in the spot oil price, producers respond by increasing the number of wells they complete today by 6%. In addition, producers respond to intertemporal relative prices: If the spot price drops relative to the 3-month future price, shale firms respond by reducing the number of wells they complete. One interpretation of this result is that producers store the oil in the ground when future market conditions look relatively better than they do at present. We find no evidence of such dynamics for conventional oil producers.

Our results thus strongly indicate that shale wells are more price elastic than conventional wells. This is a new finding in the literature. Because we first put our paper on our webpage, two other papers have been issued examining shale oil: Bornstein et al. (2018) use annual data to study production of shale producers across the United States and find slightly weaker, yet corroborate, results. Arguably, it appears that firms exploit the inherent flexibility of shale technology to allocate production volumes intertemporally and to engage in short-term below-ground storage. Newell and Prest (2019), on the other hand, find no support that shale producers behave more flexibly than conventional producers. However, neither of these papers explores well and firm characteristics, or control for future price signals, as we do here.

We interpret the results for shale oil producers to be in line with Hotelling's (1931) model of optimal exhaustible resource extraction. Reserves are an inventory, and the decision to produce is an intertemporal choice of when to draw down below-ground inventory. For producers to behave in line with the Hotelling (1931) theory, they must be able to reallocate extraction across different periods. Previous studies for conventional producers have not found this flexibility condition to hold; see, for example, Anderson et al. (2018) who found the price elasticity of oil suppliers in Texas to be zero. Our empirical results, however, show that the degree of output flexibility depends on the technology applied and that firms using shale oil technology are much more flexible in allocating output intertemporally. This enables shale producers to behave more consistently with the benchmark theories for commodity producer behavior.

The use of microeconomic data to infer the price elasticity of aggregate output has several advantages. First, by constructing a rich panel dataset, we can eliminate any potential aggregation bias over well production rates when estimating the empirical model. Aggregating over all individual wells is equivalent to imposing identical parameter values for all producing wells regardless of well or firm characteristics. In fact, when we aggregate production across individual wells in our panel and estimate supply elasticities for the two technologies, we find that aggregate output for both technologies is price-inelastic. Hence, such an approach would lead to a significant loss of information about micro-relations in our dataset. Second, the use of panel data enables us to explore the cross-sectional variation in, for instance, well type, age, location, or other characteristics of interest, and we can investigate the potential heterogeneity in producer behavior across technologies (conventional or unconventional). Third, using the large cross section of the panel, we can identify differential behavior of conventional and shale firms in response to the same price shock. Hence, our results are immune to unobserved time variation in state variables, such as changing market conditions or oil price regimes. Lastly, having a large cross section in a panel is beneficial for statistical inference when analyzing a relatively short time period as we do here.

Our results have important implications for economic outcomes and policy. First, when designing tax policies that affect the petroleum industries, policymakers should take into account that shale and conventional producers adjust differently to price-sensitive news. Second, the results have far-reaching implications for oil prices. If marginal supply are shale producers, we would eventually expect a stabilizing effect on prices as shale producers grow in size and importance; see also the discussion in Bornstein et al. (2018). Third, knowledge about the production behavior of shale oil in general becomes important, as it may affect a wide range of outcomes such as local labor market dynamics, investment, and real wages; see Allcott and Keniston (2017) and Bjørnland and Zhulanova (2018). Finally, our results have also important implications for how one should analyze the role of oil in the macroeconomy. Oil price-macro models have often assumed aggregate oil production to be price inelastic in the short run when identifying oil market shocks; compare Kilian (2009). However, as production from drilled shale wells will be responsive to shocks to the oil price also in the short term, this assumption may no longer hold. Instead, our results support exploring alternative identification schemes that relax the assumption of zero short-run response in oil production to price signals; see, for instance, Baumeister and Hamilton (2019) and Caldara et al. (2019).[3]

[3]Caldara et al. (2019) calculate the supply elasticities by minimizing the distance between the elasticities found in SVARs and some selected target values constructed from a survey of relevant studies (i.e., Hamilton, 2009), while Baumeister and Hamilton (2019) use Bayesian inference to reflect uncertainty of supply elasticity.

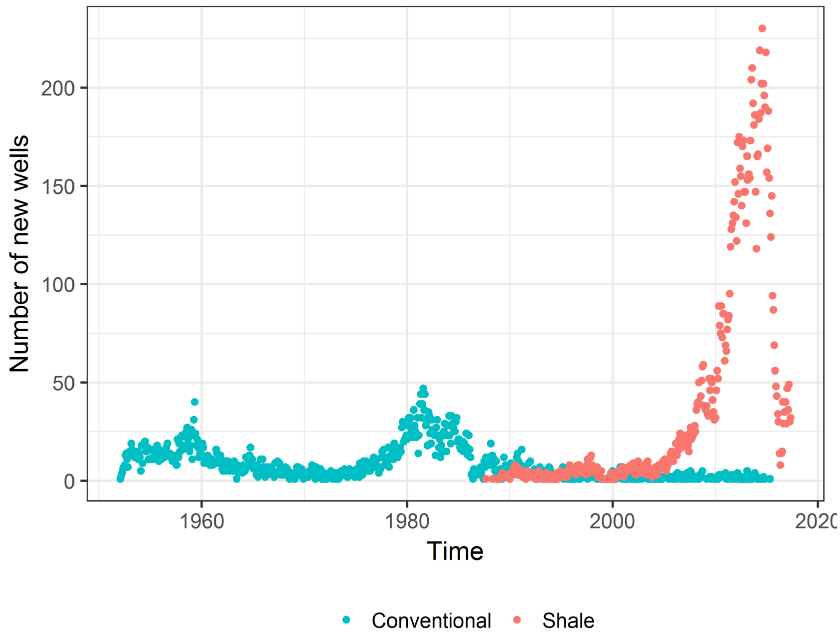


FIGURE 2 New wells entering in production over time. Note that the number of new wells entered into production on a monthly frequency in North Dakota from April 1951 to June 2017. Wells are separated into conventional/vertical wells and unconventional/horizontal/shale wells. See Section 2.2 for more details on the data [Colour figure can be viewed at wileyonlinelibrary.com]

The rest of the paper proceeds as follows: Section 2 describes the data environment. Section 3 sets up the well-level panel data model and presents the empirical results, while Section 4 defines the firm-level panel data model and presents the results from the estimations on the firm sample, before discussing wider implications of our results. Concluding remarks follow in Section 5.

2 | DATA ENVIRONMENT

Below, we provide a short background to the methods of oil extraction. We go on to explain how we identify conventional and unconventional wells, and finally we describe some key features of the dataset.

2.1 | Oil and geology in North Dakota—Background

The first commercial oil discovery in North Dakota was made in 1951 in the Williston basin. Discoveries continued in the 1960s and 1970s, and production gradually increased until it peaked during the first conventional oil boom in the early 1980s. At its peak (in 1981), 834 conventional wells were drilled in 1 year. From the peak followed a long period of decline, with only 34 wells being drilled in 1999, the lowest number of wells drilled since oil drilling began. By April 2004, production in North Dakota had also reached a minimum, at around 75,000 barrels per day.[4]

New discoveries from 2006 initiated the recent North Dakota boom. The boom relates mainly to oil deposits discovered and produced within the Bakken field, a rock formation occupying an area of about 520,000 km^2, about the size of Spain.[5] The boom started with the discovery of Parshall Oil Field in 2006, and peaked in 2012, but with substantially less growth noted since 2015; see Figure 2. The boom was made possible by the continued development of new extraction techniques. Although these techniques had existed for some time, the cost of extraction had been too high for it to be profitable. The increase in oil prices throughout the 2000s made drilling of shale oil competitive with conventional techniques, and investment in unconventional oil started to boom.

The method of oil extraction will depend on the geology of the site. *Conventional* oil well technology requires oil and gas-bearing rock that is porous, such as sandstone or washed out limestone. When crude oil forms in a permeable[6] rock, gas will naturally gather at the top of the reservoir and the crude oil will be trapped in the porous rock underneath the gas cap. At the very bottom, there is water. The crude oil is pressurized in the pores of the formation rock, so that when a well

[4]For details, see North Dakota Studies (2016).
[5]According to the US Geological Survey (USGS), see Gaswirth et al. (2013), it is the largest continuous oil resource in the lower 48 states. In April 2013, the USGS estimated that the amount of oil that could be economically recovered from the Bakken would be at 7.4 billion barrels. The formation stretches out over regions such as North Dakota, Montana, Saskatchewan, and Manitoba.
[6]Permeability is a geological term to describe how easily oil flows naturally through rock.

is drilled into the reservoir, the formation pressure and the permeability of the rock naturally drives the hydrocarbons out of the rock and up into the well. Conventional oil well technology can produce effectively from these types of reservoirs, aided by the natural pressure and the permeability in the reservoir. In practice, this involves drilling a conventional vertical well straight into the reservoir and producing the oil that flows by itself into the well; see Devold (2013) for details. The law of physics governing the flow of fluid from two locations in a porous medium with different pressures is known as Darcy's law; see Hubbert et al. (1956).

In contrast to a conventional oil reservoir, when crude oil is trapped in a rock formation that has zero permeability, the natural pressure in the reservoir formation is not enough to make the oil flow into the well once a well is drilled because the oil is trapped in small pockets inside the shale rock formation. Naturally, Darcy's law of fluid flow also applies to shale rock, but the zero permeability restricts the flow of fluid.[7] These types of reservoirs, often called tight oil reservoirs, require additional stimulation once the well has been drilled. That is, a combination of hydraulic fracturing (or "fracking") combined with horizontal drilling enables the oil to escape the rock formation. We therefore say that shale is the least permeable, meaning it must be fracked in order to be completed for production. This essentially decouples the fracking operation (completion) from the drilling operation, allowing for the type of flexibility that we document in the paper.

For both conventional vertical wells and unconventional shale wells, however, the well drilling process starts in a similar way: A rig drills a vertical well into the ground, to depths of up to 10,000 ft. For conventional vertical wells, the rig will stop drilling at this point, and the well will be completed for production as a vertical well. In shale oil wells, however, the well will be drilled further, but at an angle, creating a so-called "bend." This initiates the horizontal part of the well, which can extend up to 10,000 ft in the horizontal direction. Once the well is drilled, it is encased with a metal pipe, a so-called casing, throughout the well. This is done to keep the formation wall from caving into the well bore and to allow for control of the flow of oil to the well head. For shale wells, the drilling rig and its crew leave the site at this point. The well must then be completed, that is, fracked by a fracking crew, in order to actually start producing.

The drilling process for conventional and unconventional oil is illustrated in Figure 3, whereby the process for conventional oil entails a vertical well directly into the oil and gas bearing rock, which is under high pressure. The pressure difference between the reservoir and the wellhead is what keeps the oil flowing to the surface with natural pressure depletion. Contrastingly, for shale oil, the oil does not flow naturally to the surface but has to be released from the shale rock formations with the aid of strong water pressure in combination with chemicals and proppants.

A particular feature of the oil extraction in North Dakota is that while the conventional oil boom that peaked in the 1980s was a *vertical* drilling boom, the recent unconventional oil boom is a *horizontal* drilling boom; see, for example, Miller et al. (2008) for details. The main reason for this relates to the thickness of the middle Bakken geological layer, from which most of the shale oil is extracted. The geological layer is at most 150 ft thick, which is fairly thin for an oil producing zone; see, for example, Meissner (1984). This makes it highly inefficient to produce by vertical wells; hence, the well is drilled horizontally so more of the wellbore can be exposed to the oil producing zone.

Another important difference between shale and conventional wells is the fact that shale has a more front loaded production profile relative to conventional production. In particular, the high pressure at which oil flows out of the fractured shale rock suggests much higher initial production rates from shale oil relative to conventional oil. Hence, this increases the incentive to optimize the timing of well completion.[8] Figure 4 illustrates this. The figure graphs the average monthly production rates for the two types of well technology, plotted against well age. Table 1 displays some corresponding comparative statics. In particular, we report average exponential decline rates individually for well technology during the first few years after spudding. Subsequently, we report cross-sectional averages for well technology, conventional and shale, separately. The largest difference in decline rate is found for the first 2 years of production, when the average decline rate for shale wells is −6.52% and the corresponding rate for conventional is −3.18%, which is half that of shale wells. This means that the production profile of shale wells is substantially more front-loaded than for conventional wells. In fact, the corresponding number of months it takes for production to reach half its initial level is only 10.64 months for shale wells, while it is nearly 22 months for conventional wells. Extending the time period to the first 5 years of a well's lifespan shows a similar pattern; the decline rate for shale wells is substantially higher than for conventional wells, although the difference is largest during the first 2 years.

[7]See, for instance, oil field glossary at http://www.glossary.oilfield.slb.com/Terms/p/permeability.aspx for details.

[8]Note that after the well has started, it often needs some sort of artificial pumping to bring the oil to the surface in sufficient quantities to make the well cover variable costs. Because shale wells have a decline rate that is very high relative to conventional wells, the phase when the well needs some sort of artificial lifting unit happens at a younger well age, relative to the conventional vertical wells.

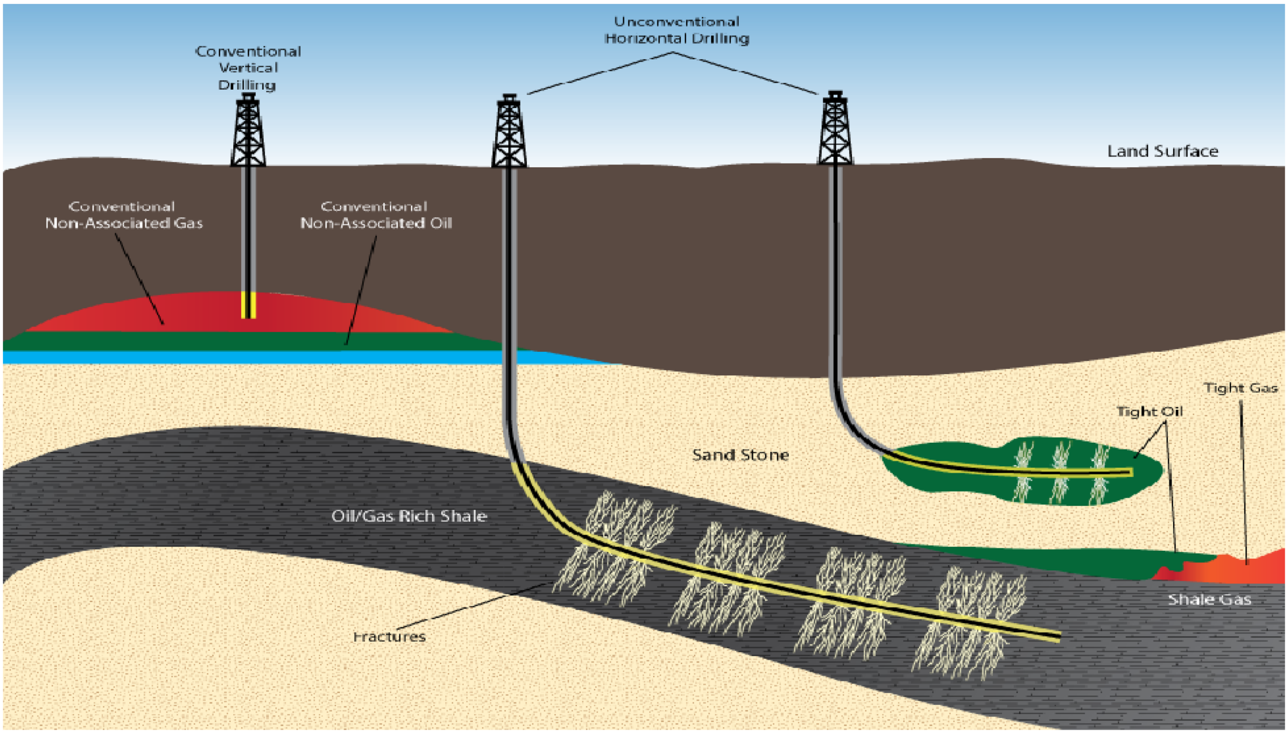
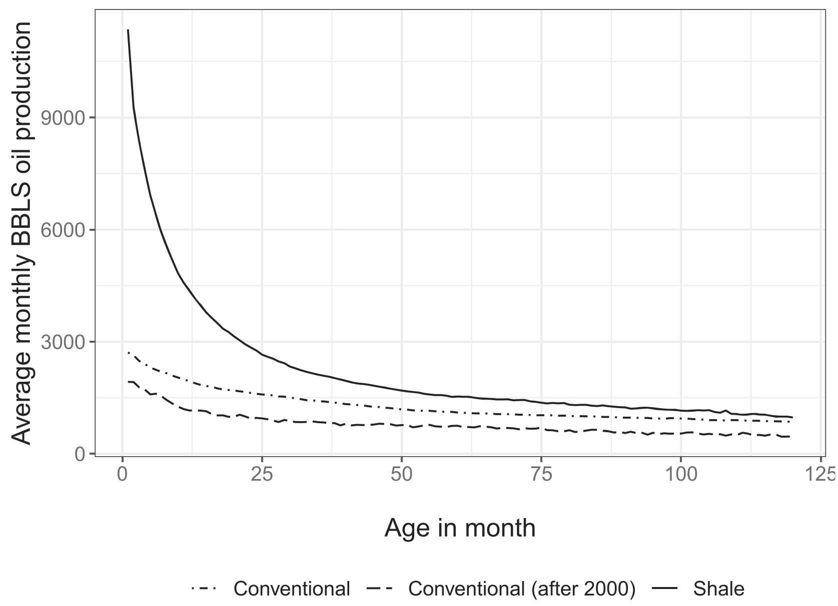


FIGURE 3 Conventional and unconventional drilling. Note: source: Curtis (2011) [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 4 Production profile of horizontal and vertical drilled wells. Note the average monthly production of BBLS oil during the first 120 months after spudding. We exclude the first month of production as wells typically do not operate every day of this month. Wells are separated in conventional/vertical wells, indicated by the blue color, and unconventional/horizontal/shale wells, indicated by the red color. The solid line cover wells spudded between February 1952 and June 2017, while the dashed line only considers conventional wells spudded after January 2000. See Section 2.2 for more details on the data



Finally, the productivity of wells, measured as the flow rate for the first month, is also different across geographies. Figure B1 in the supporting information illustrates this feature of oil wells. The figure displays the initial 2-year production of each well at their geographical position. We consider all shale wells spudded before June 2015 in North Dakota. The color indicates the aggregate oil output of the well during the first 2 years, and darker units have higher production. Well productivity appears to be highest in the central part, in the counties of Mountrail and McKenzie. There appears to be some spatial autocorrelation of well productivity, because the darkest units rarely border the lightest units. This suggests that the main determinants of well productivity are geological characteristics, which are spatially autocorrelated at this level of disaggregation.

TABLE 1 Average monthly exponential decline rate

	Conventional All	After 2000	Shale All	Conventional - shale Estimate	*p* value
Decline rate, first 5 years	−2.59%	−3.04%	−3.99%	−1.39%***	0.00
Corresponding half-life in months	26.74 m	22.82 m	17.39 m		
Decline rate, first 2 years	−3.18%	−3.64%	−6.52%	−3.34%***	0.00
Corresponding half-life in months	21.83 m	19.02 m	10.64 m		

Note: Average exponential decline rates of the form $\text{Prod}_{i,t} = \text{Prod}_{i,t-1} * e^{r}$ individually for well technology. For the 5-year production decline rates, we consider all wells that were spudded before June 2012 with at least 24 months of data, while for the 2-year production decline rates, we focus on wells spudded before June 2015 with at least 12 months of data. For conventional wells, we report the average decline rate for wells spudded after January 2000. We exclude the first production growth rate from the estimation because wells typically do not operate all days during the first month, which inflates the initial growth rate. To ease interpretation, we report half-lives implied by the estimated decline rates—the number of months it takes for production to reach half of the initial level $t^{\text{half-life}} = \log(0.5)/r$. In the last column, we report the results of a t test testing for a significant difference between the decline rate for conventional and shale wells. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

2.2 | Data and identification

The dataset used here was retrieved from the database of the North Dakota Industrial Commission (NDIC), Oil and Gas Division. It provides production figures on a monthly frequency for 16,109 crude oil wells in North Dakota.[9] The total dataset was collected for the full time period from 1952 to 2017. However, the sample period used in the analysis is limited by the availability of future oil price series and thus ranges from February 1990 to June 2017.

An important issue is how to distinguish a shale well from a conventional well in the database. As mentioned in Section 2.1, tight oil in North Dakota is found in thin geological layers, which can only be efficiently extracted using horizontal well technology (combined with hydraulic fracturing). In the data, we observe the drilling technology (horizontal vs. vertical) at well level and can thus identify shale oil production by the drilling technology.

We construct an unbalanced panel with crude oil wells as the unit of analysis. As seen in Figure 2, the recent boom in the number of wells entering into production surpasses anything previously seen in North Dakota. Furthermore, the boom is entirely caused by horizontal drilling and fracturing. Figure B1 in the supporting information further details all of North Dakota's crude oil wells from each well's geographic coordinates within the state. We note that the density of wells is high, particularly in certain areas. The shale wells appear to be drilled more closely together than conventional wells, often in an array-like pattern.

From the constructed dataset, we observe that two thirds of all wells are horizontal shale wells. The average age of a horizontal well is 63 months, whereas the average age of a conventional well is 263 months.[10] This underlines the need to control for well age in the analysis; see Table A.1 for main summary statistics. Overall, our raw data contain 570 operator firms that operated wells in the sample period, reflecting an industry structure with many small and independent firms. In our regressions, however, there are up to 338 active firms, depending on the specification. The average number of wells completed per firm in the sample period is 51, although the number of completions is highly concentrated; 80 firms account for more than 80% of the wells in the sample.

2.3 | Oil price indices: Spot and futures

The oil price series used in the analysis is the monthly average of the West Texas Intermediate (WTI) crude oil price for delivery in Cushing, Oklahoma, provided by the Energy Information Administration (EIA). The futures prices of oil are monthly averages at different time horizons, and they are from the New York Mercantile Exchange (NYMEX), and retrieved from Datastream.

We use the difference in growth rates between the spot price and the futures price for a contract with delivery at time $t + j$ to measure the expected change in market conditions between the spot market for crude oil and the future market of oil going j months ahead. If this measure is positive, the spot market looks relatively more favorable measured against the futures market than before. If it is negative, the future market going j months ahead has become relatively more favorable than before.

[9]The raw data cover more than 33,000 wells. However, after requiring that there are sufficient data observations, it reduces to 16,109.
[10]Average age for conventional is higher, as they were drilled earlier.

There are several reasons for using futures prices to measure a firm's price expectations. First, US shale producers can lock in prices for their production months into the future and then sell at opportune moments.[11] Second, NYMEX futures are traded liquidly at the time horizons considered here, and with many risk-neutral traders, the futures price should be a reasonable approximation of the expected future spot price. Also, oil well operators are believed to use the futures market to make price projections. The futures prices included in this paper are real prices, so that the annual expected price change reflects real rather than nominal changes. In addition, the future prices on the NYMEX marketplace are the reference prices that physical crude oil futures market can actually be sold at in the physical market for crude oil for future delivery.

3 | WELL PANEL

Our aim is to analyze to what extent oil producers respond to prices by changing oil production at the well level, that is, supply elasticity. To do so, we use a well panel to analyze if firms adjust the flow rate from existing wells in response to price incentives, distinguishing between conventional and shale oil wells. In all regressions, we include lagged production changes, various price signals, and a set of controls. Importantly, we include both spot prices and spot-futures spreads. As mentioned above, the futures market for crude oil provides intertemporal price signals that producers also consider closely. In particular, if spot prices increase relative to the future, we would expect the well owners to maximize profit by increasing production today, and vice versa if the spread is decreasing. We expect no relationship for conventional wells.

3.1 | Empirical framework

We start by regressing the percentage change of oil production from well i on lagged oil production, crude oil spot prices, spot-futures spreads, and additional macroeconomic controls:

$$\begin{aligned}\Delta LogProd_{i,t} = {} & \beta_0 \Delta LogProd_{i,t-1} + \beta_1 \Delta LogProd_{i,t-1} * Shale_i \\ & + \beta_2 \Delta P_t + \beta_3 \Delta P_t * Shale_i \\ & + \beta_4 \Delta (P_t - F_{t,t+3}) + \beta_5 \Delta (P_t - F_{t,t+3}) * Shale_i \\ & + X_t + \lambda_y + \mu_i + \rho_{i,t} + e_{i,t},\end{aligned} \tag{1}$$

where $\Delta Log\,Prod_{i,t}$ is the percentage change in oil production from well i and $Shale_i$ is an indicator variable equal to 1 if the well is horizontal, allowing us to estimate technology-dependent parameters. $\Delta P_t = \log(P_t/P_{t-1})$ is the percentage change in the price of crude oil and $\Delta(P_t - F_{t,t+3}) = \log(P_t/P_{t-1}) - \log(F_{t,t+3}/F_{t-1,t+2})$ is the percentage change in the log futures spot spread, where the future contract for oil is to be delivered at time $t + 3$. For both prices, we allow for different coefficients depending on whether the well is horizontal or not. X_t represents time-varying macroeconomic controls. They include the price of copper, the dollar exchange rate, and the interest rate. The idea is that these variables may capture aggregate demand, affecting both oil prices and the decision to produce oil (see Hamilton, 2014). In addition, we allow for two more macroeconomic controls that will capture general macro instability: the log changes in the VIX and the log changes of the MSCI World index. Finally, we include year fixed effects (λ_y), well fixed effects (μ_i), and individual well age fixed effects ($\rho_{i,t}$). Well fixed effects can, for example, effectively control for any time-invariant geological features of a well, such as location. $e_{i,t}$ is the error term, clustered at the time and well level. For details on data and data transformations, see Table A.1.

Importantly, we make the assumption that the oil price is exogenous to the monthly output of crude oil wells and number of wells put into production at time t in North Dakota. Similar assumptions have been made in, among others, Anderson et al. (2018) and Kellogg (2014), analyzing production and investment decisions in Texas oil drilling.[12] This is plausible for several reasons. First, because there are about 500 firms in our sample, no single firm is able to exert any market power in the global market for crude oil. Second, North Dakota is not a big player in the global oil market, and the combined production of all firms is just over one million barrels of crude oil per day, which is below 1% of global daily output. Third, the price of oil is largely determined in the global market, and the additional shale oil production coming

[11]Central banks and other policy agencies typically use future oil prices while making forecasts. In particular, the slope of the yield curves formed with these prices provide information on the direction of spot prices; see Reeve and Vigfusson (2011) for an analysis of the usefulness of future prices.
[12]See also Borenstein and Kellogg (2014) for similar assumptions, but used in a different application, analyzing to what extent the decline in relative crude oil prices in the US Midwest (i.e., WTI relative to the Brent) are passing through to wholesale gasoline and diesel prices.

from the United States in recent years is small compared to the size of the global oil market. Still, as we want to control for common factors that may also affect both the oil price and the decision to produce oil, we include a set of key macro variables in the regressions, described above. In the end, we also analyze robustness to the assumption that the oil price is exogenous by instrumenting for the oil price.

3.2 | Empirical results

Before estimating Equation (1), and in order to motivate the use of well-level data, we first aggregate output across all producing wells into two different monthly time series: one for conventional oil production and one for shale oil production. We then run two separate regressions: a regression for conventional production and a regression for shale production. Table B1 in the supporting information displays the results. All coefficients are statistically insignificant at the conventional levels of confidence. This echoes previous results in the literature that oil producers do not respond significantly to price signals. However, because we have aggregated output over individual wells, estimating supply elasticity for this production series is equivalent to imposing identical parameter values for all producing wells on either shale or conventional regardless of well or firm characteristics. This will lead to a significant loss of information about micro relations in our dataset and lead to a potential aggregation bias. Only by constructing a rich panel dataset can we eliminate any potential aggregation bias over well production rates when estimating the empirical model. We turn to this now.

The results from the estimation of Equation (1) on the full well-level panel are presented in Table 2. The panel spans 15,990 unique conventional and unconventional producing wells in North Dakota between February 1990 and June 2017, giving us a total of 1,332,178 observations.[13] Summarizing the coefficients for the response in shale oil to spot prices in Table 2, we find an elasticity for shale wells of 0.71, which is statistically significant at the 99% level. That is, for a 10% increase in the spot price of oil, shale oil production increases by 7%, which is a substantial response. Note that these results are assuming that the change in the spot futures spread is due to changes in the spot price.[14] However, in Table B3 in the supporting information, one can read off the appropriate linear combinations of the parameters to the different price signals. The results are the same and confirm our finding of a large supply elasticity. Turning to the response to a unit change in the 3-month spot futures spread, we find an elasticity of 0.83, and it is statistically significant at the 99% level. Hence, as the futures increases relative to the spot prices, producers reduce production (awaiting the higher future prices). One interpretation of this result is that producers store the oil in the ground when future market conditions look relatively better than the present. This is a new finding in the literature.

For conventional wells, the overall production response to a change in the spot price of crude oil is 0.03 but statistically insignificant, and the response to a change in the spot futures spread (due to a change in the 3-month future price) is 0.07 and insignificant. Hence, analyzing the supply responses to price signals on the well level suggests that the supply elasticity from shale wells is at least 7 times larger than the elasticity from conventional wells. The low and insignificant response of conventional oil echoes results from previous studies.[15]

Having analyzed the average response, we want to explore the rich well panel, so as to examine if response varies with the type of well producing. Table 3 shows extensions to the baseline well-panel model along several dimensions, estimating Equation (1) for the subsample of shale wells only.[16] In Column (1), we report results using weighted least squares (WLS). This addresses a concern that with ordinary least squares (OLS), we give all observations implicitly equal weight, including wells with little output. WLS puts implicitly more weight on high-volume shale oil wells. Summing together the coefficient for the variable ΔP_t and $\Delta\left(P_t - F_{t,t+3}\right)$ yields an estimated supply elasticity in response to the

[13] One could worry that the data might exhibit spatial autocorrelation in areas of similar geological characteristics. Under this scenario, individual residuals are not independent, which calls into question the validity of hypothesis tests provided. To deal with this, we conduct a sequence of tests, namely, the CD statistics following Pesaran ((2004), (2015)), Moran's I (see Moran, 1950, for original paper and Gittleman & Kot, 1990, for implementation), and bootstrapping to investigate the empirical distribution of the estimates. Given our findings, we do not find spatial correlation to be a substantial concern and proceed with clustering standard errors on year month and well level. Results can be obtained upon request.

[14] Total production response from shale wells to a change in the spot price of oil will be captured by the sum of coefficients β_2, β_3, β_4, and β_5, while the shale wells production response to a change in the spot futures spread will be captured by the sum of coefficients β_4 and β_5. The conventional wells' response to a change in the spot price will be captured by β_2 and β_4, and the response to a change in the spot futures price spread will be captured by β_4. Hence, the supply elasticity for shale is $0.03 - 0.15 + 0.07 + 0.76 = 0.71$.

[15] Note that we start the sample in 1990 as there are very few, if any, unconventional wells before 1990. However, it could be interesting to see results for conventional wells before 1990. We have therefore redone the analysis for conventional wells only from 1980. We then have to exclude futures, because they do not date back to the 1980s. Doing so, the coefficient on the spot price increases marginally to 0.05, but it is now significant.

[16] This table focuses on shale wells, as conventional wells have a lower production per well than unconventional ones. Hence, using weighted least squares (WLS) with production has the unintended effect of under weighting one production technology, conventional in this case, compared to unconventional production.

TABLE 2 Well panel: Supply elasticity—Baseline

	***Dependent variable:* Δ log $\text{Prod}_{i,t}$ (1)**
Δ log $\text{Prod}_{i,t-1}$	-0.36^{***}
	(0.005)
Δ log $\text{Prod}_{i,t-1} * \text{Shale}_i$	0.03^{***}
	(0.01)
$\Delta(P_t)$	0.03
	(0.05)
$\Delta(P_t) * Shale_i$	-0.15^{***}
	(0.05)
$\Delta(P_t - F_{t,t+3})$	0.07
	(0.20)
$\Delta(P_t - F_{t,t+3}) * Shale_i$	0.76^{***}
	(0.27)
Macroeconomic controls	Yes
Well FE	Yes
Year FE	Yes
Age FE	Yes
Unique wells	15,990
First observation	February 1990
Observations	1,332,178
Adjusted R^2	0.11

Note: Estimation results from regressing well-level oil production on price signals interacted with extraction technologies and various controls (Equation 1). For definition of the variables, see Section 3.1. The panel spans all conventional and unconventional wells in North Dakota between February 1990 and June 2017. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

spot price of 0.77, and the estimate is significant on the 99% level. Also, the supply response to a change in the spot futures spread is 0.91 and statistically significant.

Second, we split the wells in two different groups based on the age of the wells; Column (2) shows results for a group of young wells, that is, wells between 3 and 36 months, and Column (3) shows the results for the group of older wells, that is, wells older than 36 months. The supply elasticity for young wells to changes in the spot price of oil is now at 0.97, while the estimated response to a change in the spot futures spread is 1.15. For wells with age more than 36 months, the corresponding elasticities are at 0.55 and 0.68. Hence, the younger wells are on average 76% more price-elastic than their older counterparts, with respect to changes in the spot price. This is a new finding in the literature.

Third, in Column (4), we scrutinize the quality of the data. In particular, as there are some months that have missing observations, there is a concern that results could be driven by data issues due to missing observations. We define high quality as wells where there are no observations missing in the first 5 years. The elasticity estimate for the response to changes in the spot price is 0.64, which is close to the baseline estimate. Also, the response to a change in the spot futures spread is 0.75, which is also fairly close to the baseline.[17]

Additional tests of robustness are made in Table 4. In Column (1), we add lagged spot prices to analyze if firms respond to past price signals rather than only future signals. We do not find past price signals to be significant, and including these lags does not change the baseline results, if anything, the coefficient increases somewhat. In Columns (2) and (3), we replace 3-month future price with the 6-month and 12-month future prices, respectively. As can be seen, the production response is somewhat smaller in magnitude when including future prices at longer horizons, but the response is still

[17]The correlation between our main variables, changes in the spot and the spread, is 0.605. Although this is not high, in the presence of imperfect multicollinearity, coefficients will be imprecisely estimated but unbiased. We investigate the stability of our point estimates using bootstrapping. In particular, we re-estimate the model 250 times using a re-sample with replacement approach with $N = 20\%$ of the original sample. For both coefficients, we find a very narrow empirical confidence interval.

TABLE 3 Well panel: Supply elasticity—Extensions

	Dependent variable: Δ log $\text{Prod}_{i,t}$			
	WLS log($\text{Prod}_{t,i}$) (1)	$\text{Age}_{i,t} \in 3 \ldots 36$ m (2)	$\text{Age}_{i,t} > 36$ m (3)	High quality (4)
Δ log $\text{Prod}_{i,t-1}$	−0.34***	−0.33***	−0.33***	−0.33***
	(0.01)	(0.01)	(0.01)	(0.004)
$\Delta(P_t)$	−0.14*	−0.18*	−0.13*	−0.11*
	(0.08)	(0.09)	(0.08)	(0.06)
$\Delta(P_t - F_{t,t+3})$	0.91***	1.15***	0.68**	0.75***
	(0.30)	(0.31)	(0.31)	(0.24)
Macroeconomic controls	Yes	Yes	Yes	Yes
Well FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Unique wells	12,490	12,488	8896	5144
Observations	704,457	378,462	325,995	455,932
Adjusted R^2	0.15	0.10	0.10	0.11

Note: Extensions of the model in Equation (1), regressing well-level oil production on price signals interacted with extraction technologies and various controls. In Model (1), we use weighted least squares (WLS) estimation with log $\text{Prod}_{i,t}$ as weight. In Model (2), we limit the panel to the initial 36 months of each individual well. In Model (3), we limit the panel to observations 36 months after spudding. In Model (4), we limit the panel to observation in the initial 5 years after spudding for wells that have complete data in that time period. For definition of the variables, see Section 3.1. Here, we focus on all unconventional wells in North Dakota between February 1990 and June 2017. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

statistically significant. In particular, when we include either the 6- or 12-month future spot spread, the supply elasticity declines to 0.5 and 0.3, respectively.[18]

One of the main concerns regarding the empirical setup is that supply factors in the United States could influence the price of oil, creating a reverse causality problem. In order to filter away potential supply shocks from the oil price series and look at demand-driven oil price movements, we regress the oil price on a set of key variables that capture common macro factors and then use the predicted value of WTI (rather than WTI) in the regressions for oil production, replacing both the changes in oil prices and the spread. The result of this exercise can be viewed in Column (6).[19]

Results are robust to using the instrumented oil price, and the supply elasticity is still large and significant. Overall, the robustness tests are reassuring.

4 | FIRM PANEL

So far, we have analyzed the responses at the well level. However, the de facto decision makers with respect to production from individual wells will in most instances be the firms. They operate the wells. However, the speed of transition from conventional to shale oil technology differs between firms, as can be seen in Figure B3 in the supporting information. This figure details the time-varying share of shale wells for a subset of firms in our data. Although some firms appear to have made a rapid shift from conventional to shale, others show a gradual approach. Also, some firms have a minority of their wells placed in shale areas, while the majority is placed in conventional reservoirs. This suggests that firms may behave differently to price signals, depending on the share of shale wells. We therefore now turn to analyze the firm-level responses of production. Thereafter, we examine if firms optimize the completion of new wells per firm, in response to

[18]Table 4 is also limited to unconventional wells as this is the main focus of our analysis. However, a version including conventional wells as well as interaction terms can now be found in Table B4 in the supporting information. Results are robust to the inclusion of conventional wells.

[19]To capture the global macro factors behind oil price movements, we follow Hamilton (2014) and regress the changes in oil prices on the price of copper, the dollar exchange rate, and the interest rate. The idea is that if in a given period copper prices rose, the dollar depreciated, and interest rates rose, then it is likely oil prices rose as well; see Hamilton (2014) for details. Hence, we estimate following regression: $\Delta[P_t] = \beta_0 + \beta_1 \Delta i + \beta_2 \Delta USD_{tw} + \beta_3 \Delta[P_t^c]$ with $\Delta[P_t]$ defined as the change in WTI, $\Delta\, i$ as the change in the Fed-fund rate as obtained through Bloomberg, ΔUSD_{tw} as the change in trade-weighted USD rate (TWEXB) as obtained through Fred database, and $\Delta\, [P_t^c]$ as the change in copper prices, as obtained though Bloomberg. Table B2 in the supporting information shows the predicted regression.

TABLE 4 Well panel: Supply elasticity—Extensions cont

	Dependent variable: Δ log Prod$_{i,t}$			
	Add. lags (1)	$F_{t,t+6}$ **(2)**	$F_{t,t+12}$ **(3)**	**Proj.** P_t **(4)**
Δ log Prod$_{i,t-1}$	-0.33^{***}	-0.33^{***}	-0.33^{***}	-0.33^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta(P_t)$	-0.18^{**}	-0.22^{**}	-0.27^{**}	-0.15^{*}
	(0.09)	(0.10)	(0.12)	(0.08)
$\Delta(P_{t-1})$	-0.01			
	(0.05)			
$\Delta(P_{t-2})$	-0.03			
	(0.06)			
$\Delta(P_t - F_{t,t+3})$	0.96^{***}			0.93^{***}
	(0.30)			(0.29)
$\Delta(P_t - F_{t,t+6})$		0.77^{***}		
		(0.22)		
$\Delta(P_t - F_{t,t+12})$			0.60^{***}	
Macroeconomic controls	Yes	Yes	Yes	Yes
Well FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Unique wells	12,395	12,490	12,490	12,490
Observations	682,624	704,457	704,457	704,457
Adjusted R^2	0.10	0.10	0.10	0.10

Note: Robustness for the model in Equation (1), regressing well-level oil production on price signals interacted with extraction technologies and various controls. In Model (1), we use additional lags for $\Delta(P)$. In Models (2) and (3), we use longer term futures. In Model (4), we use projected $\Delta(P)$. The first stage can be found in Table B2 in the supporting information. For definition of the variables, see Section 3.1. Here, we focus on all unconventional wells in North Dakota between February 1990 and June 2017. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

price incentives. The decision to complete a well is equivalent to exercising the real option to produce, because this is the actual start of production from a well; see also Appendix C in the supporting information for details.

4.1 | Empirical framework: Supply elasticity and well completions

In order to analyze the response from production on the firm level, we aggregate the output from wells by firm and obtain a sample of up to 338 firms from February 1990 to June 2017. Similar to Equation (1), we estimate the following equation, but now for the percentage change of oil production from firm i:

$$\begin{aligned}\Delta Log\,Prod_{i,t} = {} & \beta_0 \Delta Log\,Prod_{i,t-1} + \beta_1 * Shale\,tech_{i,t-1} \\ & + \beta_2 \Delta Log\,Prod_{i,t-1} * Shale\,tech_{i,t-1} \\ & + \beta_3 \Delta P_t + \beta_4 \Delta P_t * Shale\,tech_{i,t-1} \\ & + \beta_5 \Delta(P_t - F_{t,t+3}) + \beta_6 \Delta(P_t - F_{t,t+3}) * Shale\,tech_{i,t-1} \\ & + X_t + \lambda_y + \mu_i + e_{i,t},\end{aligned} \tag{2}$$

where $\Delta Log\,Prod_{i,t}$ is the percentage change of oil production from firm i and $Shale\,tech_{i,t-1}$ is the share of oil produced from horizontal wells to total oil of firm i at time $t-1$. It is a time-varying measure, between 0 and 1, meant to capture the intensity of shale technology used by individual firms over time. ΔP_t, $\Delta(P_t - F_{t,t+3})$ and X_t follow the definition from Section 3.1. Finally, we include year fixed effects (λ_y) and firm fixed effects (μ_i). $e_{i,t}$ is the error term, clustered at the time and firm level. Note that we include $Shale\,tech_{i,t-1}$ in the regression to control for structural differences in production changes associated with a high share of unconventional wells versus a low one. For example, during the sample period

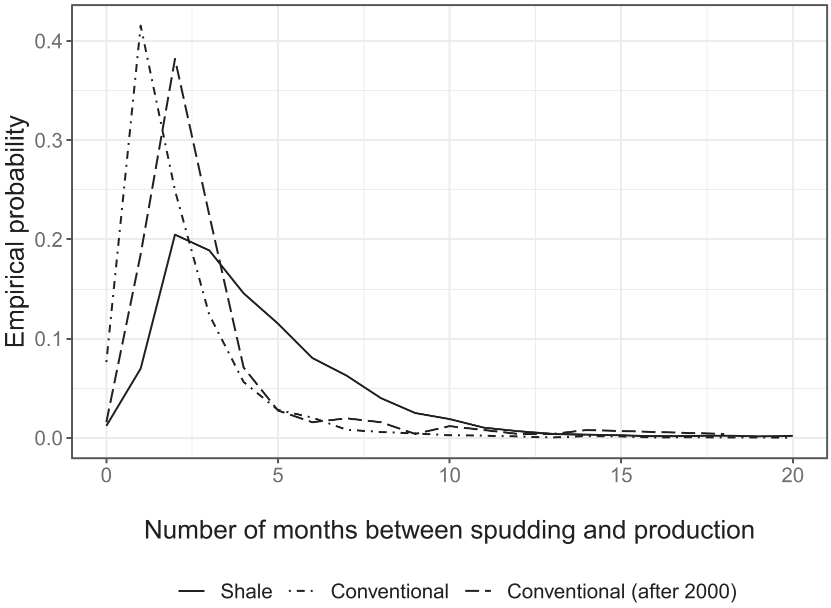


FIGURE 5 Production profile of conventional and shale wells. Note the empirical distribution of the delay between spudding a well (drilling) and the first month of production, measured in months. Wells are separated in conventional/vertical wells, indicated by the blue color, and unconventional/horizontal/shale wells, indicated by the red color. The solid line cover wells spudded between February 1952 and June 2017, while the dashed line only considers conventional wells spudded after January 2000. See Section 2.2 for more details on the data

a higher share of unconventional wells is likely associated with a positive change in production or increased number of new wells.

Following the analysis of production at the firm level, we examine if firms optimize the completion of new wells per firm, in response to price incentives. As explained above, the timing of when to *start production* is different from the timing of when to *start drilling* the well. The reason is that wells are frequently drilled but left uncompleted for a certain time. Once a well is completed, however, it starts producing. Thus, we define a well as completed the moment it completes its first month of production. To do so, we use a firm-level panel data model, comparing again the two types of well technologies. We postulate that shale firms more often than conventional wells leave wells that are drilled uncompleted or in below-ground storage. These are assets that can be quickly liquidated when markets are favorable. The steep production profile of shale wells provides an incentive to optimize the timing of completion. Hence, we should expect to see a delay between the time a well is spudded (drilled) and the first production month. Figure 5 illustrates this. It displays the empirical probability function of delay between spudding a well and the first month of production, measured in months. The figure illustrates that on average there is a longer gap between drilling/spudding for shale wells than for conventional. In addition, the distribution is more dispersed; that is, variation is larger.

In sum, this supports the idea that deciding to complete a well is a choice variable, which motivates studying supply elasticity on the extensive margin. In particular, if there is a positive relationship between firms' monthly well completions and an increase in the 3-month spot-futures spread, firms decrease the rate of completions when future prices are expected to be higher than the spot price today (i.e., a negative spot-futures spread), effectively leaving oil in the ground awaiting a higher price. To test this more formally, we turn to the firm-level panel data model, where we estimate the following equation:

$$\begin{aligned} Log(New\,wells_{i,t}) = {} & \beta_0\, Log(Inventory_{i,t-1}) \\ & + \beta_1\, Log(Producing\,wells_{i,t-1}) + \beta_2\, Shale\,tech_{i,t-1} \\ & + \beta_3 \Delta P_t + \beta_4 \Delta P_t * Shale\,tech_{i,t-1} \\ & + \beta_5 \Delta\,(P_t - F_{t,t+3}) + \beta_6 \Delta\,(P_t - F_{t,t+3}) * Shale\,tech_{i,t-1} \\ & + X_t + \lambda_y + \mu_i + e_{i,t}, \end{aligned} \tag{3}$$

where $Log(New\,wells_{i,t})$ represents the log of new wells completed by firm i at time t, $Log(Inventory_{i,t-1})$ is the number of wells drilled by firm i at time $t-1$ that are not yet in production, and $Log(Producing\,wells_{i,t-1})$ is the number of producing wells operated by firm i at time $t-1$. ΔP_t, $\Delta\,(P_t - F_{t,t+3})$, $Shale\,tech_{i,t-1}$, and X_t are defined above. Finally, we include year fixed effects (λ_y) and firm fixed-effects (μ_i). e_{it} is the error term, clustered at the time and firm level. Below, we display results from estimating production of oil and completion of wells per firms in North Dakota.

TABLE 5 Firm panel: Supply elasticity and completion—Baseline

	Dependent variable:	
	Δ log($\text{Prod}_{i,t}$)	**log(New $\text{wells}_{i,t}$ + 1)**
	(1)	(2)
log($\text{Inventory}_{i,t-1}$ + 1)	0.03***	0.66***
	(0.01)	(0.03)
Δ log($\text{Prod}_{i,t-1}$)	−0.31***	
	(0.01)	
log(Producing $\text{wells}_{i,t-1}$ + 1)		0.08***
		(0.01)
$Shaletechnology_{i,t-1}$	0.01	0.09***
	(0.01)	(0.02)
$\Delta(P_t)$	0.14**	0.01
	(0.06)	(0.01)
$\Delta(P_t - F_{t,t+3})$	−0.48	−0.01
	(0.33)	(0.04)
$\Delta(P_t) * Shaletechnology_{i,t-1}$	−0.20**	−0.17**
	(0.09)	(0.08)
$\Delta(P_t - F_{t,t+3}) * Shaletechnology_{i,t-1}$	1.47***	0.77***
	(0.40)	(0.30)
Macroeconomic Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Unique firms	333	338
Observations	49,532	51,001
Adjusted R^2	0.09	0.72

Note: Results of regressing the production per firm (Equation 2) and the number of new wells per firm (Equation 3) on price signals and various controls in Columns (1) and (2), respectively. $New\ wells_{i,t}$ represents new wells completed by firm i at time t, $Shaletechnology_{i,t}$ is defined as the ratio of oil produced by fracking wells of firm i to total oil produced by firm i at time t. $Inventory_{i,t}$ is the number of wells spudded by firm i that are not yet in production. $Producingwells_{i,t}$ is the number of producing wells by firm i at time t. Note that the inventory and producing wells (raw variables) are skewed to the right and have many 0 observations. Hence, in order to make the variables normally distributed and not lose the zero observations, we use a $log(X + 1)$ transform. For definition of the remaining variables, see Section 3.1. The panel spans all firms producing oil in North Dakota between February 1990 and June 2017. For each firm, we only consider the months between the first time they spudded a well until the last production observation. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

4.2 | Empirical results

We report the results from estimating firm-level responses. Table 5, Column (1), shows the results from the estimation of Equation (2), which is estimating production per firms, while Column (2) presents the results from the estimation of Equation (3), analyzing well completions by firms. Starting with Column (1), the response of a firm's production whose well portfolio at time $t-1$ consisted entirely of shale wells to a change in the spot price is 0.93, which is somewhat higher than the well-level estimate of supply elasticity but very close to the well-level supply elasticity for shale wells younger than 36 months. Note that this is the response to a change in the spot price only and assumes no change in the future price.[20] The response of firms' production to a change in the spot futures spread is 0.99, which is fairly close to the baseline estimate found for the well-level panel. Hence, when aggregating production by firm, which is plausibly the most relevant decision-maker with respect to production decisions, we find a strong and positive supply elasticity.

Column (2) shows the results for well completion per firm. The estimated elasticity of supply with respect to putting new wells on stream to changes in the spot price of oil is 0.6, which is somewhat lower than the supply elasticity found for well-level production. Still, this is a fairly large response to a unit increase in the oil price. Hence, overall, and for both production and well completions, firms appear to respond significantly positively to spot prices, and more so the more intensively they use shale technology. This is a new finding in the literature.

[20]Calculation: 1.47 + 0.14 − 0.2 − 0.48 = 0.93.

TABLE 6 Firm panel: Completion—Extensions

	Dependent variable: **log(New wells$_{i,t}$ + 1)**			
	Month FE (1)	**Proj. P_t (2)**	**2000+ (3)**	**WLS log(Prod$_{t,1}$) (4)**
log(Inventory$_{i,t-1}$ + 1)	0.65***	0.65***	0.61***	0.64***
	(0.03)	(0.03)	(0.03)	(0.03)
log(Producing wells$_{i,t-1}$ + 1)	0.08***	0.08***	0.10***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
$Shaletechnology_{i,t-1}$	0.08***	0.08***	0.11***	0.12***
	(0.02)	(0.02)	(0.03)	(0.03)
$\Delta(P_t) * Shaletechnology_{i,t-1}$	−0.16**	−0.05	−0.17**	−0.19**
	(0.07)	(0.07)	(0.08)	(0.09)
$\Delta(P_t - F_{t,t+3}) * Shaletechnology_{i,t-1}$	0.68**	0.32***	0.83**	0.81**
	(0.27)	(0.10)	(0.34)	(0.33)
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Unique firms	338	338	205	338
Observations	51,001	51,001	27,705	51,001
Adjusted R^2	0.72	0.72	0.74	0.74

Note: Robustness for the model in Equation (3), regressing the number of new wells per firm on price signals and various controls. In Model (1), we add month fixed effects, which we keep for all specifications reported. In Model (2), we use projected $\Delta(P)$. In Model (3), we limit the data to post 2000. In Model (4), we use weighted least squared estimation with log Prod$_{i,t}$ as weight. The first stage can be found in Table B3 in the supporting information. Note that the inventory and producing wells (raw variables) are skewed to the right and have many 0 observations. Hence, in order to make the variables normally distributed and not lose the zero observations, we use a $log(X + 1)$ transform. For definition of the variables, see Section 3.1 and Table 5. The panel spans all firms producing oil in North Dakota between February 1990 and June 2017. For each firm, we only consider the months between the first time they spudded a well until the last production observation. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

We now dig deeper and extend the results for well completions along several dimensions; see Table 6. First, in Column (1), we add month fixed effects, to control for any aggregate time-varying factors other than the oil price indices, which could influence well completion decisions. As can be seen, the response to price changes remains strong and statistically significant. The well completion response of firms is not, therefore, caused by other macroeconomic developments than the oil price changes. Second, Column (2) shows results using again the projected oil price, where changes in the price of copper are used to proxy for changes in global demand. As can be seen, the coefficient for the change in the spot futures spread is statistically significant also for this exercise, and our result does not seem to be driven by supply shocks in the oil market, potentially stemming from the US shale production. In Column (3), we study only the period after the year 2000, which is, after all, the period in which the shale technology really proliferated. The coefficients are not greatly affected, and the well completion supply elasticity is still large and significant. Finally, in Column (4), we estimate a regression where larger weight is assigned to firms with a higher number of wells. This is to make sure our results are not only caused by small and insignificant producers. As can be seen, the coefficients also here do not change noteworthily.

Table 7 shows the results of additional robustness tests. One conjecture about firms is that major oil operators with professional organizations are better able to take advantage of price movements than small firms. In Column (1), we limit the sample to the 99 firms with the highest production volume. As can be seen, the results remain in line with our baseline estimation, and the well completion response is, if anything, stronger for the largest firms. In Column (2), we show results for the remaining firms in the sample. Now the results change, and the supply response is no longer statistically significant. This suggests that our results are driven mainly by the firms that are large. Small firms do not change their response due to price signals. They either come on stream or not. In Column (3), we check whether our results are sensitive to the definition of shale technology. Instead of using the share of oil produced from shale wells to total oil of firm i at time t, we use the ratio of shale wells of firm i to total wells at time t. Although the coefficients are slightly reduced in magnitude, the response of firms is still strong and statistically significant. In Column (4), we define the shale technology variable as the ratio of oil produced by shale wells of firm i to total oil produced from time t. Also for this definition of shale technology, our results remain statistically significant. Overall, our results do not seem to be sensitive to the specific definition of the intensity of shale technology in use by firms.

TABLE 7 Firm panel: Completion—Extensions cont

	Dependent variable: **log(New wells$_{i,t}$ + 1)**			
	Top 99 firms (1)	**Remaining firms (2)**	**Shale tec. 2 (3)**	**Shale tec. 3 (4)**
log(Inventory$_{i,t-1}$ + 1)	0.64***	0.26***	0.65***	0.66***
	(0.03)	(0.06)	(0.03)	(0.03)
log(Producing wells$_{i,t-1}$ + 1)	0.09***	−0.01***	0.08***	0.05***
	(0.01)	(0.003)	(0.01)	(0.01)
$Shaletechnology_{i,t-1}$	0.10***	0.002	0.09***	0.18***
	(0.03)	(0.01)	(0.03)	(0.05)
$\Delta(P_t) * Shaletechnology_{i,t-1}$	−0.27**	−0.01	−0.13*	−0.16*
	(0.10)	(0.03)	(0.07)	(0.08)
$\Delta(P_t - F_{t,t+3}) * Shaletechnology_{i,t-1}$	1.17***	−0.03	0.53*	0.56*
	(0.42)	(0.09)	(0.27)	(0.32)
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Unique firms	338	338	205	338
Observations	22,689	28,312	51,001	56,146
Adjusted R^2	0.72	0.10	0.72	0.72

Note: Robustness for the model in Equation 3, regressing the number of new wells per firm on price signals and various controls. In Model (1), we limited the sample to the 99 firms with the highest production volume. In Model (2), we consider the remaining firms. In Models (3) and (4), we use alternative specification of the shale technology variable. Shale tec. $2_{i,t}$ is defined as the ratio of fracking wells of firm i to total wells at time t. Shale tec. $3_{i,t}$ is defined as the ratio of oil produced by fracking wells of firm i to total oil produced from time $t0:t$. All specifications include month fixed effects. For definition of the variables, see Section 3.1 and Table 5. The panel spans all firms producing oil in North Dakota between February 1990 and June 2017. For each firm, we only consider the months between the first time they spudded a well until the last production observation. Standard errors reported in brackets are clustered on well level and months. *Significantly different from zero at the 90% level, **Significantly different from zero at the 95% level and ***Significantly different from zero at the 99% level.

4.3 | Wider implications and related studies

We interpret our results for shale oil producers to be in line with Hotelling's (1931) model of optimal exhaustible resource extraction. Reserves are an inventory, and the decision to produce is an intertemporal choice of when to draw down below-ground inventory to above-ground inventory, stored in pipelines, oil terminals, and refinery facilities. In particular, the Hotelling (1931) model assumes resource owners are forward-looking and maximize wealth by trading extraction today for extraction in the future. Crucially, Hotelling's price path is only achieved when producers enjoy complete flexibility regarding when to produce.

Our empirical results indicate that the degree of output flexibility depends on the technology applied and that firms using shale oil technology are more flexible in allocating output intertemporally. For producers to fully comply with the classic theory, one should then observe that production is reduced to 0 when expected price growth exceeds the nominal interest rate, and vice versa when prices are expected to grow below the risk-free rate. Although well-flow rates in our data are rarely reduced to 0, using the futures price as a proxy for the expected spot price, our results indeed suggest that shale-well technology allows producers to allocate production more in line with what the classic Hotelling theory predicts as the optimal response to deviations from the Hotelling price path. Hence, we believe the pattern reported in this paper is consistent with Hotelling's theory of how resource extraction firms should respond to deviations from Hotelling's price path. Most importantly, we have shown that oil suppliers could respond to higher *expected* oil prices by storing oil *below* the ground. Shale producers have this option, for technological reasons, as they may drill, but not frack a well in anticipation of rising prices. We have shown in an extensive analysis that these drilled but uncompleted wells (DUCs) do indeed respond strongly to price signals, suggesting that production could also be a choice variable. For instance, to efficiently schedule well completions, producers maintain a reasonable number of DUCs for operational flexibility and/or economic reasons, as pointed out by EIA (2019). Thus, our reported findings, that oil firms respond to price signals by *completing wells*, are not only important, but they also suggest that the results we have found for production are credible.[21]

[21] In a recent paper, Kilian (2020) questions our results, arguing that data do not support a positive correlation between DUCs and the oil futures spread. However, our paper contains no empirical results directly concerning DUCs. We analyze completions, as opposed to drilling, the other choice variable

Our results for shale are in contrast with recent literature on conventional oil. Notably, Anderson et al. (2018) have shown that the price elasticity of conventional oil producers in Texas is statistically indistinguishable from 0. They present a strong argument that the relevant conventional control variable for oil firms is exploration investment, not flow production. However, the production of horizontally drilled shale oil differs from conventional operations. As mentioned above, the option of executing DUCs suggests a plausible mechanism through which shale oil firms may respond to price developments by increasing production. That said, focusing on conventional oil well only, our results of a short-run supply elasticity of 0.05 for conventional producers in North Dakota is consistent with the results reported by Anderson et al. (2018) for conventional oil producers in Texas.

Since we first put our paper on our webpage, two other studies have been issued analyzing shale oil supply responses: Bornstein et al. (2018) study production of shale producers across the United States using annual data and find corroborate, albeit somewhat weaker results, probably due to the low-frequency data. Still, it appears that firms exploit the inherent flexibility of shale technology to allocate production volumes intertemporally and to engage in short-term below-ground storage. Newell and Prest (2019) analyze all the distinct phases of well development, that is, drilling, completion, and production for shale producers in five different states. Doing so, they find the short-run supply elasticity to be 0. However, for completion and investment, they find shale wells to respond positively to price signals. Interestingly, Newell and Prest (2019) include future prices in their analysis, as we do, but only for drilling and completions. To be precise, they use the average of the next 12 months of futures prices for the WTI and Henry Hub prices instead of the spot prices in the parts that analyze drilling and completion of the wells (see Newell & Prest, 2019 p. 5), while they use only the spot prices when they analyze well production. Hence, Newell and Prest (2019) base all their models with positive results on futures prices, while for production, where they exclude futures, they do not find any significant results.[22]

Finally, our results have important implications for how one should analyze the role of oil in the macroeconomy. In particular, as production from drilled shale wells will be responsive to shocks to the oil price also in the short term, assuming an inelastic short-run elasticity of supply is implausible. Instead, our results support exploring alternative identification restrictions that allow for short-run responses; see, for instance, Baumeister and Hamilton (2019) and Caldara et al. (2019). Furthermore, a simple back-of-the-envelope calculation shows that during the sample we are examining, our estimates can encompass a parameter space that supports short-run elasticities of the magnitudes estimated in Baumeister and Hamilton (2019) and Caldara et al. (2019) (for total oil supply). Such parameters give implied shares of shale oil in global oil production varying between 9% and 25% the last decade; see Table B6 in the supporting information. These numbers seem reasonable given the share of shale in world production in recent time.[23] Prior to the recent US fracking boom, however, the share of shale oil in total production was negligible. Thus, although our estimated parameters for shale oil elasticity point to short-run average elasticity that is in line with what was found in Baumeister and Hamilton (2019) and Caldara et al. (2019), another parameter space (from, i.e., earlier periods) would point to a short-run elasticity that is slightly lower.

5 | CONCLUSION

The recent coronavirus pandemic and subsequent global crisis have seen oil prices falling abruptly to 0. In the midst of the crisis, the US administration has announced it is considering to buy oil that producers leave in the ground until prices recover. At that point, the producers extract and sell the oil for a higher price than the government paid them and then repay the government, see FT (2020).

How is this possible? This paper has shown how. It has shown that output flexibility in oil production depends on the extraction technology. For shale oil, reserves are an inventory, and the decision to produce is an intertemporal choice of when to draw down below-ground inventory. In particular, we have quantified large and substantial differences in the response of crude oil output to price signals between conventional and shale oil wells in North Dakota. In particular, shale wells increase the monthly production by 7% for a 10% increase in the spot price. Furthermore, we also document that producers respond to intertemporal relative prices; if the spot price drops relative to the 3-month futures price, meaning

in the DUCs. This is lost when using a linear combination of drilling and completions, as Kilian ((2020)) does when analyzing DUCs directly. See Appendix C in the supporting information for further discussion.

[22]There are additional differences between Newell and Prest (2019) and our study, related to specification and the fact that they do not explore well and firm characteristics, as we do here. We refer the readers to Bjørnland (2019) for a discussion of the literature.

[23]According to OPEC (2019), the projection for non-OPEC crude oil supply sees shale oil's share (from the United States and the rest of the world) of non-OPEC oil output increase from 15%–16% today to 25%–26% in 2030–2035).

the price curve moves toward a contango situation, shale firms respond by reducing the number of wells they complete. We find no such evidence for conventional oil. Finally, we document that the output pattern of shale oil wells is consistent with the Hotelling theory of optimal extraction. For the behavior of conventional oil wells, we find no such evidence.

To the best of our knowledge, this study is the first to investigate the price elasticity of shale oil production on the well level and to compare it with conventional oil production. As the share of unconventional oil production increases, it is important to have good estimates of price elasticity of supply, for example, when designing tax policies for the oil industry. It is also necessary to have knowledge about the production behavior of shale oil in general, as it may affect a wide range of outcomes such as local labor market dynamics, investment, oil supplies, and prices.

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This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at [http://qed.econ.queensu.ca/jae/datasets/bjornland002/].

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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APPENDIX A: SUMMARY STATISTICS

TABLE A1 Summary statistics

Panel A: Time series variables	**Mean**	**Standard deviation**	**Observations**
Δvix_t	−0.24%	14.66%	329
r_t^{msci}	0.38%	3.69%	329
$\Delta(P_t)$	0.21%	8.59%	329
$\Delta(P_t - F_{t,t+3})$	−0.03%	2.00%	329
Δi_t	−0.63%	12.68%	329
ΔUSD_t^{tw}	0.00%	1.66%	329
$\Delta(P_t^{\text{Copper}})$	0.27%	6.28%	329

Panel B: Well-level data	**All wells**		**Shale wells**		**Conventional wells**	
	Mean	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Observations	1,366,466		726,629		639,837	
Number of wells	16,109		12,575		3534	
Number of formations	34		26		29	
Number of firms	337		119		296	
Age in month	152.0	160.0	46.0	46.0	274.0	156.2
$\Delta(\log \text{Prod}_{i,t})$	−2.0%	61.0%	−3.0%	68.0%	−1.0%	51.8%

Note: Panel A presents summary statistics of all time series variables used in this paper. Panel B provides summary statistics on the well-level data from oil production in North Dakota, separated into conventional and shale wells. Δvix_t is the return on the VIX index. r_t^{msci} is the return on the MSCI world index. $\Delta(P_t)$ is defined as the log price change $\log(P_t) - \log(P_{t-1})$ of the West Texas intermediate (WTI) Cushing Crude Oil Spot Price P_t obtained from the EIA. $\Delta(P_t - F_{t,t+X})$ is defined as the change in log futures spot spread $\log(P_t/F_{t,t+X}) - \log(P_{t-1}/F_{t-1,t-1+X})$ with $F_{t,t+X}$ as Nymex Crude Oil Futures Price at t obtained through Datastream. Log changes in the fed fund rate Δi_t, the trade weighted USD index using major currencies ΔUSD_t^{tw}, and copper prices $\Delta(P_t^{\text{Copper}})$ are obtained from the St. Louis Federal Reserve. The aforementioned variables are monthly averages. $\Delta \log \text{Prod}_{i,t}$ is the log change in oil production for well i between $t-1$ and t. $Age_{i,t}$ is the age of well i in months relative to the first production month. The sample spans February 1990 to June 2017.