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The effect of oil and gas price and price volatility on rig activity in tight formations and OPEC strategy

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The Effect of Oil and Gas Price and Price Volatility on Rig Activity in Tight Formations and OPEC Strategy

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Supplementary Information

Supplementary Note 1. GARCH Models

To explore the effect of price volatility on the rig count, we follow the standard econometric practice[1] of using a generalized autoregressive conditional heteroskedasticity GARCH(1,1) model to estimate conditional volatilities. The general specification of a GARCH(p,q) model is:

$$Y_t = \varepsilon_t \qquad \text{(Supplementary Equation 1)}$$

in which Y_t represents the return ($\frac{P_t - P_{t-1}}{P_{t-1}}$) to real prices for crude oil or natural gas that are calculated from monthly observations of real prices for crude oil or natural gas on spot and futures markets. We specify returns because they are used by previous efforts and the Hotelling[2] model assumes that real returns are constant over time.

From Supplementary Equation 1, ε_t can be modeled as follows:

$$\varepsilon_t = \sigma_t z_t \qquad \text{(Supplementary Equation 2)}$$

in which z_t is i.i.d. with zero mean unit variance.

The conditional variance process of a GARCH(p,q) process, σ_t^2, is specified as:

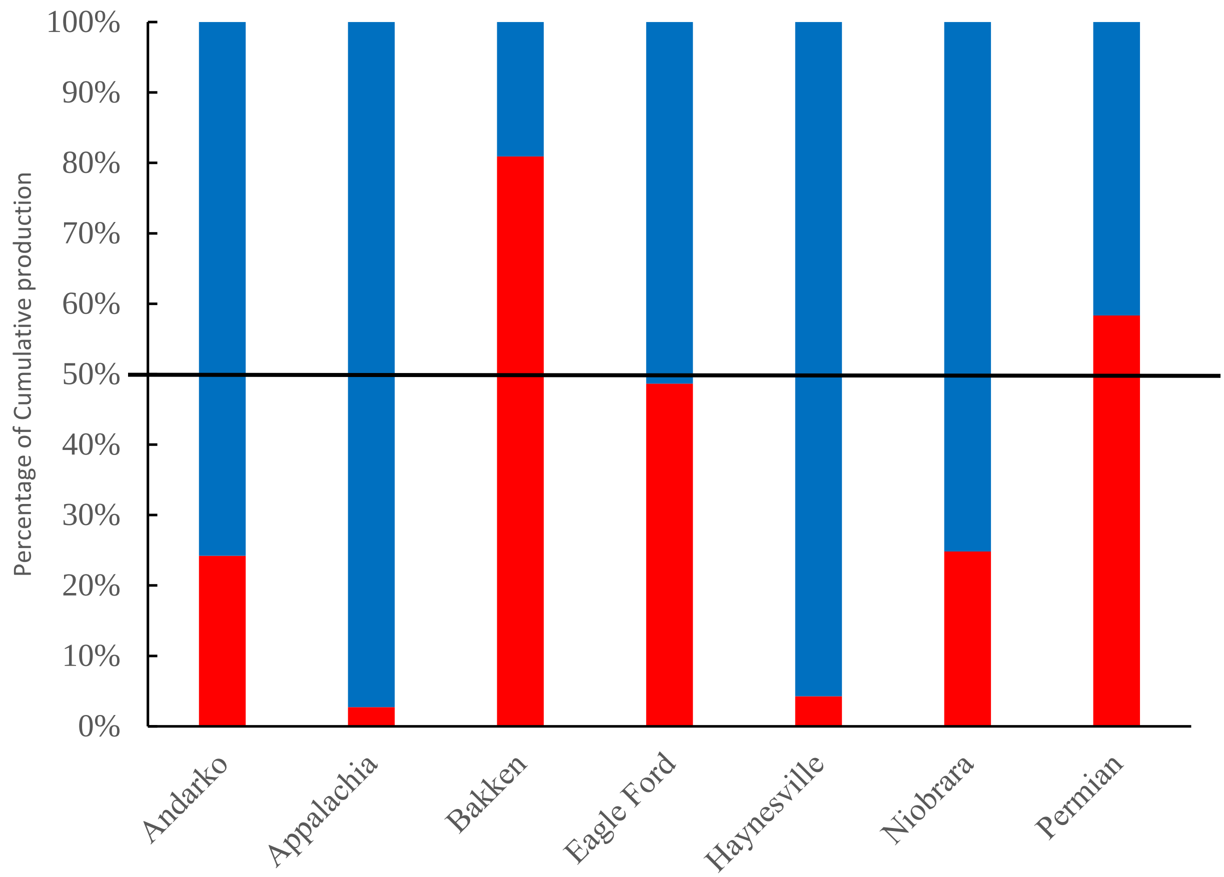
$$\sigma_t^2 = \mu + \sum_{i=1}^{p} \alpha_i \, \sigma_{t-i}^2 + \sum_{j=1}^{q} \omega_j \, \varepsilon_{t-j}^2 \qquad \text{(Supplementary Equation 3)}$$

in which $\sqrt{\sigma_t^2}$ represents the conditional volatility of the underlying price series (*Vol*).

Supplementary Note 2. Separating rig activity into oil and natural gas wells

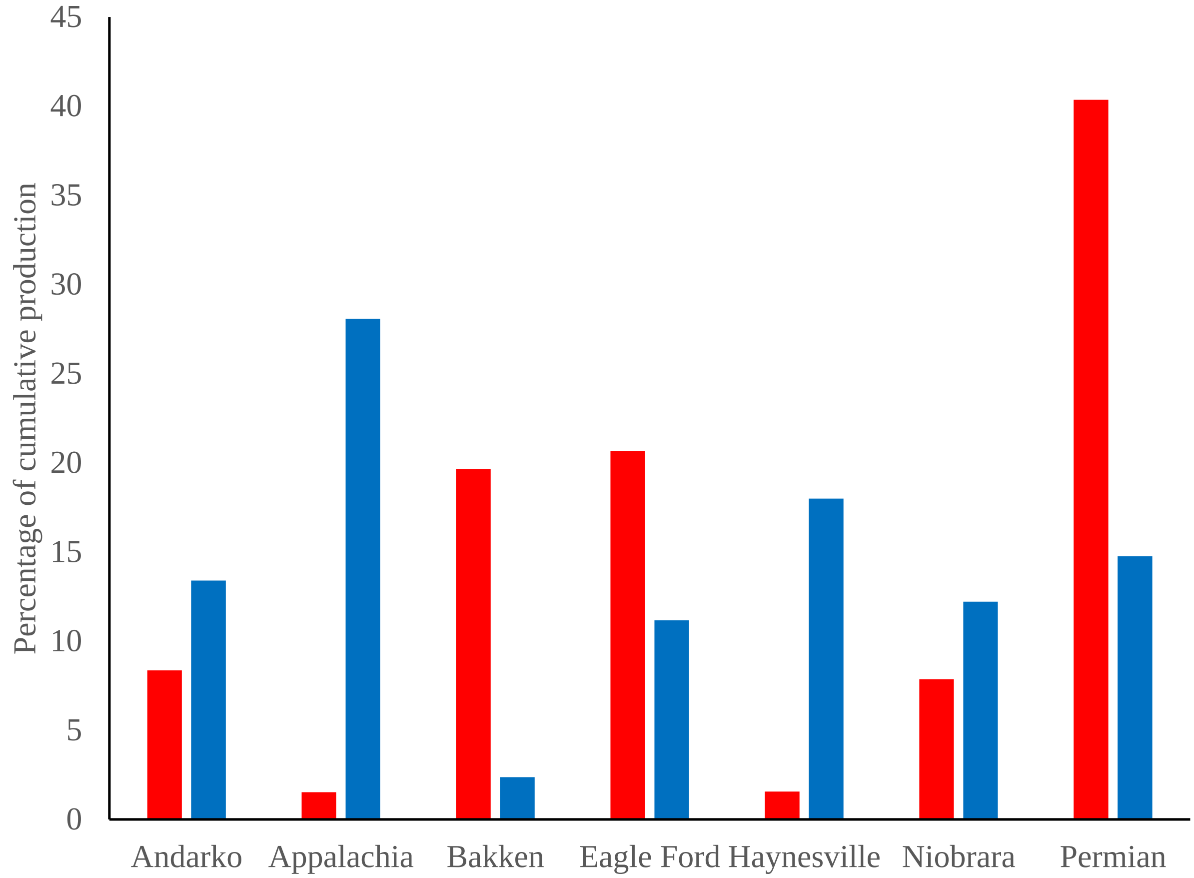
The Drilling Productivity Report[3] does not separate active rigs between those that are used to drill oil wells from those that are used to drill gas wells. Because the economics of drilling oil wells differs from the economics of drilling gas wells, we separate these activities. In summary, we identify regions where the production of one fuel dominates and use these regions to represent the economics of drilling oil wells vs. the economics of drilling natural gas wells.

To identify regions where one fuel dominates, for each region we sum monthly oil and natural gas production between January 2007 and October 2017 (the entire sample period), convert physical production to BTU, and calculate the fraction of cumulative production from oil (red areas in Supplementary Figure 4) and natural gas (blue areas in Supplementary Figure 1).



Supplementary Figure 1 The percent of cumulative production from oil vs. natural gas The percentage of each region's cumulative production of oil and natural gas, as measured in BTU, that comes from oil (red area) and natural gas (blue area) during the sample period. Data from the drilling productivity report.

Based on these results, we represent the economics of drilling oil wells by activity in the Bakken and Permian basins, where oil production represents 81 and 58 percent of cumulative production respectively. Although oil represents about 58 percent of cumulative production in the Permian region, we choose this region to represent the economics of drilling oil wells because it produces a little more than 40 percent of the total quantity of oil produced in the seven regions (Supplementary Figure 2).



Supplementary Figure 2 The percent of cumulative oil or natural gas production by region The percentage of cumulative oil production in the seven regions by each region (red bars) and the percentage of cumulative natural gas production in the seven regions by each region (blue bars) during the sample period. Data from the drilling productivity report.

We represent the economics of drilling gas natural gas wells by activity in the Appalachia and Haynesville regions, where natural gas accounts for 97 and 96 percent of cumulative energy production. These two regions also are responsible for the greatest shares of total production of natural gas in the seven regions, 28 and 18 percent respectively (Supplementary Figure 2). In the other regions, cumulative production is split more evenly between oil and natural gas (Supplementary Figures 1 & 2), and so activity in these regions is not part of the analysis.

Supplementary Note 3. Results for the 100 CVAR models for oil and natural gas

Of the one hundred CVAR models for rigs used to drill oil wells, we fail to reject the null hypothesis of zero cointegrating relations in one model ($20 BEP, one-month future contract) and fail to reject the null hypothesis that *Rig* is weakly exogenous in thirty-five models. These results indicate that 36 CVAR models do not contain a statistically meaningful long-run relation for rig activity and so we do not impose over-identifying restrictions. All of the sixty-four models that remain have one cointegrating relation that includes *Rig* and the element of α loads this cointegrating relation into the equation for ΔRig in a way that moves *Rig* towards the equilibrium value that is implied by the cointegrating relation.

For all one hundred CVAR models for rigs used to drill gas wells, we reject the null hypothesis of zero cointegrating relations and the null hypothesis that *Rig* is weakly exogenous. For each of these one hundred models, there is one cointegrating relation that contains *Rig* and the element of α loads this cointegrating relation into the equation for ΔRig in a way which moves *Rig* towards the equilibrium value that is implied by the cointegrating relation.

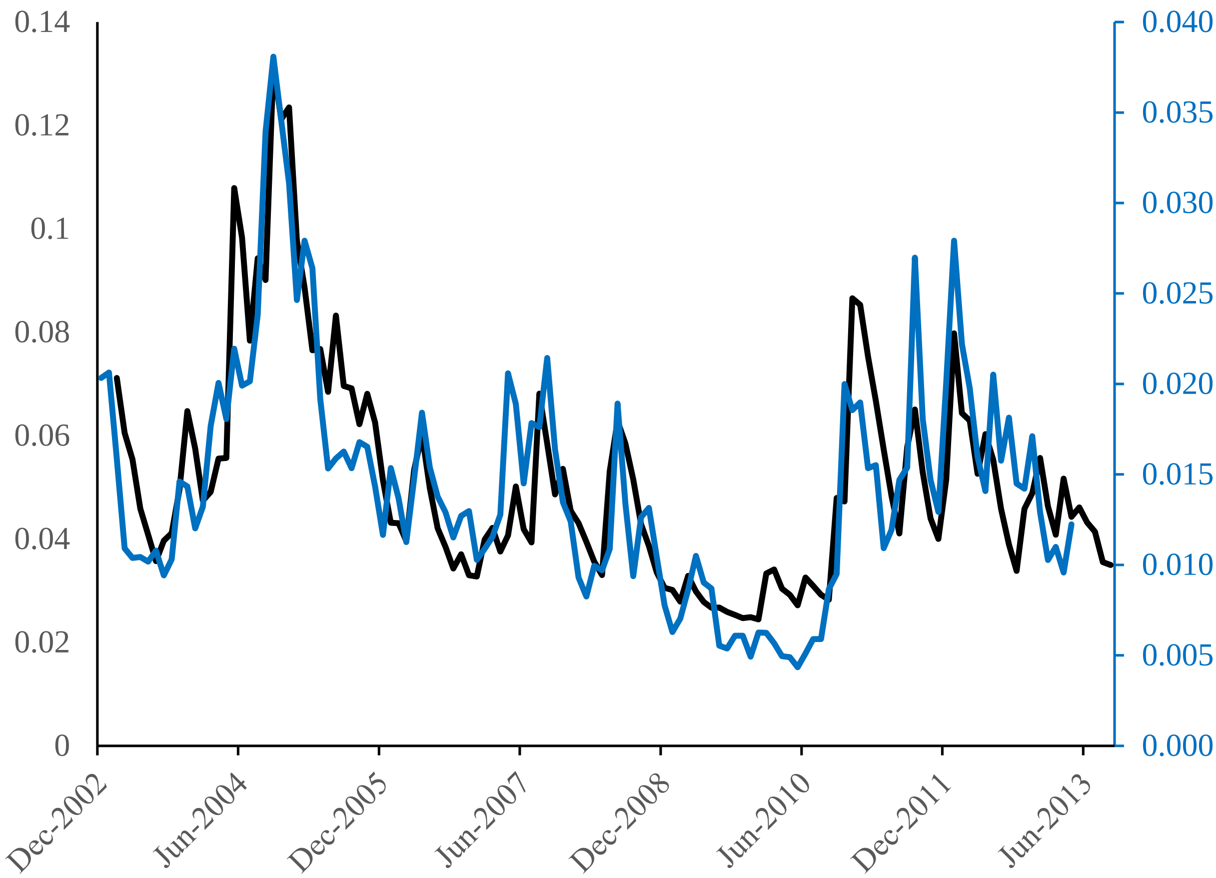
The initial comparison of all in-sample forecasts identifies a single 'most accurate' model for ΔRig used to drill oil and gas wells. In both cases, head-to-head comparisons indicate that the model selected from among all models is not the most accurate. The CVAR model that most accurately represents the number of rigs used to drill oil wells is identified by four sets of head-to-head comparisons. Two sets of head-to-head comparisons are needed to identify the CVAR model that most accurately represents the rigs used to drill gas wells. The most accurate model for oil has an r^2 of 0.843 for the rig equation, which is slightly smaller than the highest r^2 (0.846) for the rig equation in any model. The most accurate model for natural gas has the largest r^2 (0.718) for the rig equation.

Supplementary Note 4. The effect of sample size and autocorrelation on the estimate for price volatility

Recent papers suggest that GARCH models may require between 500[4] and 3,000[5] observations to avoid substantial bias. Either of these thresholds is greater than the 128 monthly observations for returns that are available for the sample period analyzed here.

To investigate the degree to which the 128 monthly observations for returns that are used to estimate volatility affect our results, we repeat (some) of the analysis with a measure of volatility that is estimated from 2,626 daily observations for price between January 2, 2007 and May 31, 2017. This sample is slightly shorter than the sample period used in the main text because we obtain the daily data before finalizing the econometric methodology (purchasing new data is expensive). We use these 2,626 daily values to calculate a daily time series for real rates of return. Daily returns are used to estimate a time series for daily price volatility from a GARCH(1,1) model. The diagnostic statistics of the GARCH(1,1) model estimated from the 2,626 daily observations are similar to those estimated from the 128 monthly observations (see Supplementary Material Note 3). A unit root test[6] 0.02 rejects ($p < .01$) the null hypothesis that the residual contains a unit root, the ARCH statistic 0.04 fails to reject ($p > 0.85$) the null hypothesis that there are no ARCH effects, and the Ljung-Box statistic 2.32, fails to reject ($p > 0.12$) the null hypothesis that the residuals are uncorrelated. Conversely, the Jarque Bera test 338.6 rejects ($p < .01$) the null hypothesis that the skewness and excess kurtosis are zero.

Daily estimates for volatility are averaged to create monthly values. Visual inspection indicates that the time series for monthly volatility that is derived from daily observations is very similar to the time series for monthly volatility that is derived from monthly observations (Supplementary Figure 3).



Supplementary Figure 3 Measures of price volatility The monthly measure of price volatility that is estimated from the shortened period of monthly observations of the price of crude oil on the futures contract with a twenty four month maturity date (black line left Y axis) and the monthly measure of price volatility that is estimated from 2,626 daily observations of the price of crude oil on the futures contract with a twenty-four month maturity date (blue line right Y axis).

This similarity suggests that using 2,626 daily observations (as opposed to 128 monthly observations) to construct the time series for price volatility will not change the results reported in the main text.

We test this hypothesis several ways. First, we test whether the two time series for price volatility cointegrate. To do so, we estimate the following regression

$$Vol_t = \alpha + \beta VolD_t + \mu_t \qquad \text{(Supplementary Equation 4)}$$

in which *Vol* is the time series for volatility estimated from the 128 monthly observations, *VolD* is the time series for volatility that is estimated from the 2,626 daily observations, α and β are regression coefficients estimated using OLS, and μ is the regression residual. A test statistic[6] 1.02 strongly (p < .01) rejects the null hypothesis that the residual (μ) contains a unit root. This result implies that the two series for volatility are cointegrated. Cointegration is critical because the CVAR model focuses on cointegration. If two time series cointegrate, replacing one time series with another time series should have relatively little effect on the results of a CVAR model.

We test this hypothesis by using the time series for price volatility that is estimated from 2,626 daily observations to re-estimate the 'most accurate' CVAR model for crude oil, which has a $20 BEP and measures oil prices using the future contract with a two-year maturity. This model also is re-estimated because the sample period is slightly shorter than the sample period reported in the text. The shorter sample period does not affect the results. A Z[1] statistic (-0.51, p > 0.61) indicates that we cannot reject the null hypothesis that the coefficient associated with *Vol* in the cointegrating relation for *Rig* estimated from the original sample period equals the coefficient associated with *Vol* in the shortened sample period.

We then use the time series for *Vol* and *PerVol* estimated from 2,625 daily observations to re-estimate the most accurate CVAR model for the number of rigs used to drill oil well. The results indicate that using the monthly time series for *Vol* and *PerVol* that are estimated from daily

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[1] $$Z = \frac{\bar{\bar{\beta}}_{original} - \bar{\bar{\beta}}_{shorter}}{\sqrt{\sigma^2_{\bar{\bar{\beta}}_{original}} + \sigma^2_{\bar{\bar{\beta}}_{shorter}}}}$$

in which $\bar{\bar{\beta}}_{original}$ *and* $\bar{\bar{\beta}}_{shorter}$ are the corresponding elements of the cointegrating relation estimated by the CVAR model that specifies measures of volatility that are estimated from the original monthly and shorter sample periods and $\sigma^2_{\bar{\bar{\beta}}_{original}}$ *and* $\sigma^2_{\bar{\bar{\beta}}_{shorter}}$ are their respective standard errors.

observations has little effect on the results relative to the CVAR model that uses the monthly time series for *Vol* and *PerVol* that are estimated from the shortened sample of monthly observations. A Z statistic[2] indicates that the coefficient associated with *Vol* in the cointegrating relation for *Rig* that is estimated using the time series for *Vol* that is calculated from 2,626 daily observations is not statistically different (Z = 8.86E-04, p > 0.99) from the coefficient associated with *Vol* in the CVAR model that uses a time series for *Vol* that is estimated from the shortened sample of monthly observations. Furthermore, the elements of the α matrix that load disequilibrium in the cointegrating relation for *Rig* (CR #1 in Table 1) into the Δ*Rig* equation are not statistically different (Z = 0.03, p > 0.97). Finally, the explanatory power of the two models is very similar. The Δ*Rig* equation in the CVAR model that specifies *Vol* and *PerVol* estimated from the shortened sample of monthly observations has an r^2 of 0.839; the corresponding value is 0.838 for the Δ*Rig* equation in the CVAR model that specifies *Vol* and *PerVol* estimated from the 2,626 daily observations.

Together, these results suggest the using the time series for *Vol* and *PerVol* that are estimated from 128 monthly observations does not have a significant effect on the results from the CVAR models that are reported here.

As described in Supplementary Note 5 and Supplementary Table 4, the Ljung-Box Q statistic rejects the null hypothesis that the autocorrelations of residuals are zero for two measures of natural gas prices and all measures of oil prices. This suggests the residuals from these GARCH

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[2] $$Z = \frac{\bar{\bar{\beta}}_{Monthly} - \bar{\bar{\beta}}_{Daily}}{\sqrt{\sigma^2_{\bar{\bar{\beta}}_{Monthly}} + \sigma^2_{\bar{\bar{\beta}}_{Daily}}}}$$

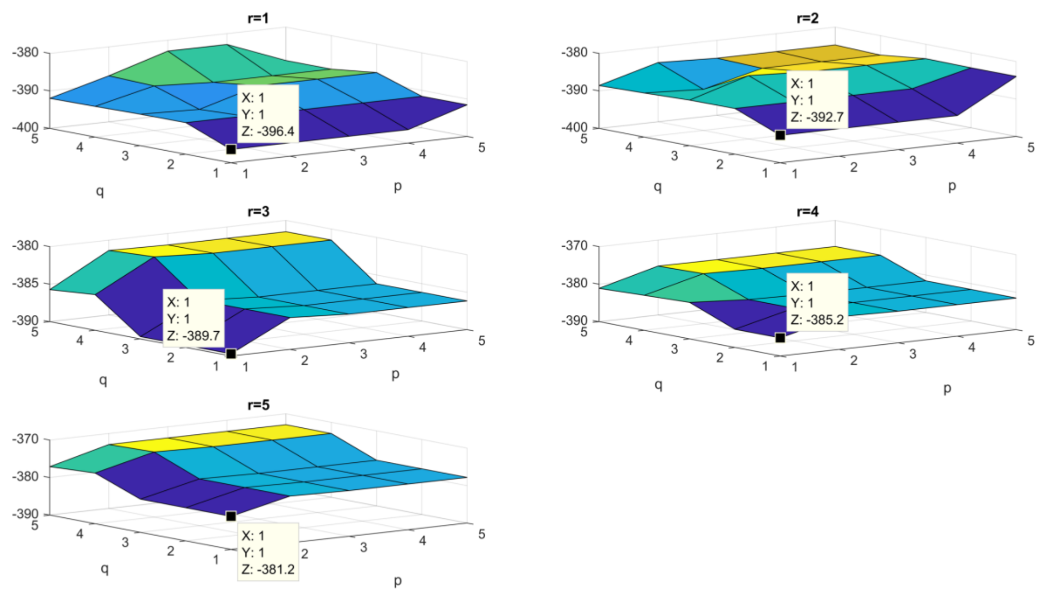
in which $\bar{\bar{\beta}}_{Monthly}$ and $\bar{\bar{\beta}}_{Daily}$ are the corresponding elements of the cointegrating relation estimated by the CVAR model that specifies measures of volatility that are estimated from monthly and daily observations respectively and $\sigma^2_{\bar{\bar{\beta}}_{Monthly}}$ and $\sigma^2_{\bar{\bar{\beta}}_{Daily}}$ are their respective standard errors.

models are autocorrelated. To evaluate the potential effects, we extend Supplementary Equation 1 by adding an autoregressive component, which creates an AR(r)-GARCH(p,q) representation:

$$Y_t = \alpha + \sum_{r=1}^{R} \beta_r Y_{t-r} + \varepsilon_t \qquad \text{(Supplementary Equation 5)}$$

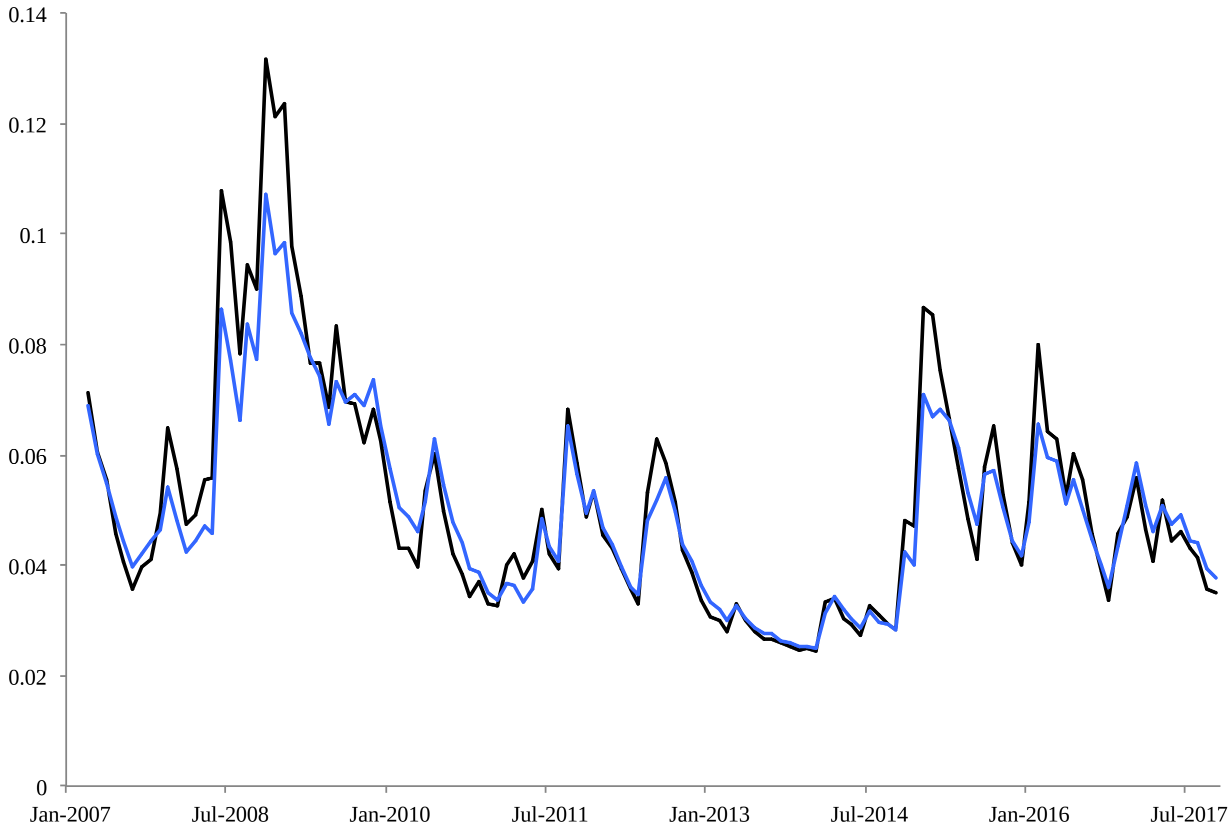
in which Y represents the daily return $(\frac{P_t - P_{t-1}}{P_{t-1}})$ to crude oil prices and ε_t comes from a GARCH(p,q) process.

To determine the best lengths for r, p and q we use the Bayesian information criteria (BIC). To compare BIC values, we estimate an AR(r)-GARCH(p,q) model with all combinations for r = 1:5 , p=1:5 and q =1:5 The BIC values suggest the best fit at r=1, p=1, q=1 (Supplementary Figure 4).



Supplementary Figure 4 BIC values of an AR(r)-GARCH(p,q) for returns of (real) WTI 24 Month Prices.

Based on these results, we use a AR(1)-GARCH(1,1) model to estimate the conditional volatilities of the returns of WTI. Supplementary Figure 5 suggests that the AR(1)-GARCH(1,1) model generates conditional volatilities that are very similar to those generated by the GARCH(1,1) model, which we use to generate the results reported in the main text.



Supplementary Figure 5 Measures of price volatility The monthly measure of price volatility that is estimated using the GARCH(1,1) model from monthly observations of the price of crude oil on the futures contract with a twenty four month maturity date (black line) and the monthly measure of price volatility that is estimated using the AR(1)-GARCH(1,1) model from monthly observations of the price of crude oil on the futures contract with a twenty-four month maturity date (blue line).

We evaluate these similarities with the same techniques that are described above. First we test whether the time series for volatility estimated by the AR(1)-GARCH(1,1) model cointegrates with the time series for volatility estimated by the GARCH(1,1) model from monthly observations. A test statistic[6] 1.524 strongly rejects ($p < .01$) the null hypothesis that the residual contains a unit root. This suggests that the two time series for volatility cointegrate.

Next we use the time series for volatility estimated by the AR(1)-GARCH(1,1) model to estimate the most accurate CVAR model for rigs use to drill oil wells. The results indicate that using the monthly time series for *Vol* and *PerVol* that are estimated by a AR(1)-GARCH(1,1) model from monthly observations has little effect on the results relative to the CVAR model that uses the monthly time series for *Vol* and *PerVol* that are estimated by a GARCH(1,1) model as reported in the main text. A Z statistic indicates that the coefficient associated with *Vol* in the cointegrating relation for *Rig* that is estimated using the time series for *Vol* that is estimated by an AR(1)-GARCH(1,1) model is not statistically different ($Z = 0.61$, $p > 0.54$) from the coefficient associated with *Vol* in the CVAR model that uses a time series for *Vol* that is reported in the main text. Furthermore, the elements of the α matrix that load disequilibrium in the cointegrating relation for *Rig* (CR #1 in Table 1) into the ΔRig equation are not statistically different ($Z = 0.11$, $p > 0.91$). Finally, the explanatory power of the two models is very similar. The ΔRig equation in the CVAR model that specifies *Vol* and *PerVol* estimated from monthly observations has an r^2 of 0.839; the corresponding value is 0.845 for the ΔRig equation in the CVAR model that specifies *Vol* and *PerVol* estimated from the AR(1)-GARCH(1,1) model.

Together, these results suggest the using the time series for *Vol* and *PerVol* that are estimated from an GARCH(1,1) model that shows signs of autocorrelation does not have a significant effect on the results from the CVAR models that are reported here.

Supplementary Note 5. Diagnostic statistics for the GARCH(1,1) model used to estimate volatility

Tests of the residuals from the GARCH model (Supplementary Equation 3) suggest that it can be used to proxy the volatility of oil and gas prices (Supplementary Table 4). Test statistics[6] reject the null hypothesis that the residuals from each GARCH model for oil and natural gas prices contain a stochastic trend, which indicates that the residuals are stationary. The ARCH statistic fails to reject the null hypothesis that there are no ARCH-effects for all measures of oil and gas prices, which indicates there is little evidence for conditional heteroscedasticity and volatility. Most of the Jarque Bera tests fail to reject the null hypothesis that skewness and the excess kurtosis are zero, which suggests residuals of the GARCH model come from a normal distribution. The Ljung-Box Q statistic rejects the null hypothesis that the autocorrelations of residuals are zero for two measures of natural gas prices and all measures of oil prices. This suggests the residuals from these GARCH models are autocorrelated. We explore the potential effects of this autocorrelation by adding an autoregressive component to the GARCH model (see Supplementary Note 3).

Supplementary Note 6. Asymmetric responses to volatility

Recent analyses suggest that markets react more strongly to volatility during periods of high volatility[7]. To investigate this hypothesis, we; (1) calculate the residual from the cointegrating relation for ΔRig, (2) decompose this residual based on the level of price volatility, (3) specify the decomposed residual in an error correction model, and (4) test whether rig activity responds symmetrically to disequilibrium[8].

In the first step, we calculate disequilibrium, which is represented by the residual (μ) in the cointegrating relation for *Rig* (CR #1 in Table 1) for oil and natural gas, which is calculated as follows:

$$\mu_t = Rig + 1.053 * Vol \qquad \text{(Supplementary Equation 6)}$$

$$\mu_t = Rig + 1.731 * PerVol - 1.711 * Profit - 4.204 * Revenue - 3.947 * NWP \quad \text{(Supplementary Equation 7)}$$

and decompose this disequilibrium based on whether volatility is above or below its sample mean as follows:

$$\mu_t^+ = \left(Vol_t \geq \overline{Vol}\right) * \mu_t \qquad \text{(Supplementary Equation 8)}$$

$$\mu_t^- = \left(Vol_t < \overline{Vol}\right) * \mu_t \qquad \text{(Supplementary Equation 9)}$$

in which μ_t^+ and μ_t^- have a value of zero for months in which the Boolean logic is false. The decomposed time series for disequilibrium are specified in an unrestricted error correction model, which is given as follows:

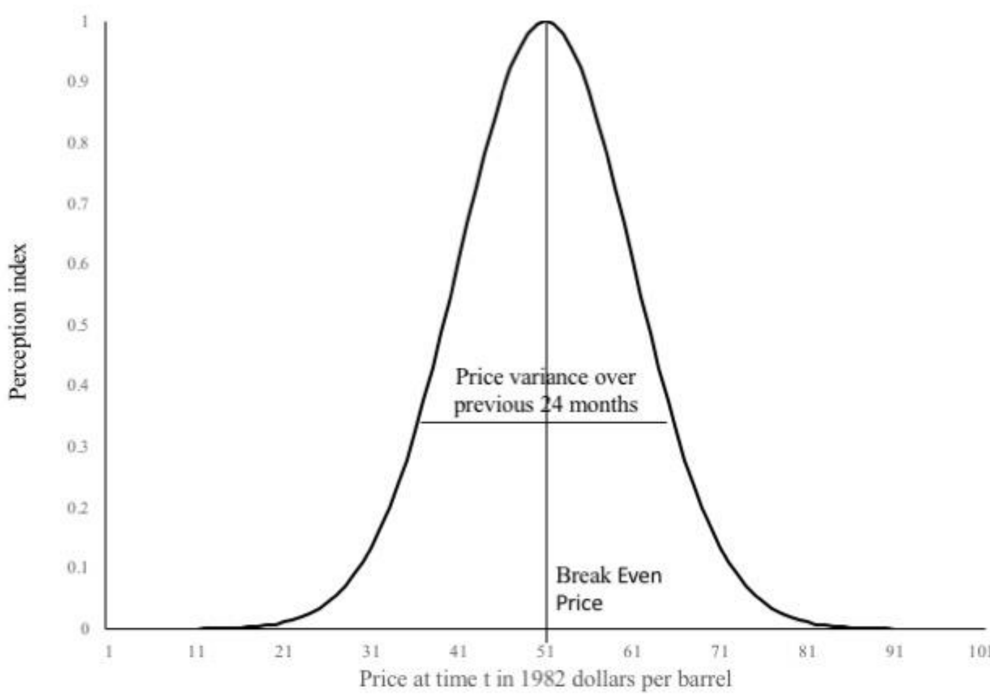
$$\Delta Rig_t = \alpha + \rho^- \mu_t^- + \rho^+ \mu_t^+ + \sum_{j=1}^{s} \gamma_j Rig_{t-j} + \sum_{j=1}^{s} \theta_j \Delta Profit_{t-j} + \sum_{j=1}^{s} \phi_j \Delta Vol_{t-j} + \sum_{j=1}^{s} \psi_j \Delta PerVol_{t-j} + \sum_{j=1}^{s} \xi_j \Delta Revenue_{t-j} + \sum_{j=1}^{s} \Psi_j \Delta NWP_{t-j} + \upsilon_{i,t} \qquad \text{(Supplementary Equation 10)}$$

in which the lag length s is chosen using the Akaike information criterion[9] and the standard errors are calculated using a procedure that is robust to the presence of serial correlation and heteroskedasticity in the error term[10].

To test whether *Rig* adjusts towards equilibrium faster (or slower) when volatility is above its sample mean, we impose the restriction ($\rho^- = \rho^+$) and test it with the F-form of the Wald test, which can be evaluated against a χ^2 distribution with one degree of freedom. This test statistic has a low power to reject the null hypothesis which suggests that $p < 0.1$ may represent cases in which the null hypothesis is rejected[11].

Results for the most accurate CVAR model for rigs used to drill oil wells indicate that the Wald fails to rejects the null hypothesis ($\chi^2(1) = 2.38,\ p > 0.12$), which indicates that the rate at which *Rig* adjusts towards the equilibrium implied by the cointegrating relation does not depend on whether *Vol* is above or below its sample mean. Similarly, we fail to reject the null hypothesis that *Rig* adjusts symmetrically to disequilibrium in the cointegrating relation for the number of rigs used to drill gas wells ($\chi^2(1) = 0.14,\ p > 0.71$).

Together, these results are not consistent with the hypothesis that the rate of drilling for oil or natural gas reacts more strongly during periods of high volatility.



Supplementary Figure 6 Normalized perception index The perception index is calculated from a normal distribution in which the mean is given by the break-even price and the variance of the perception index is given by the variance of price over the previous 24 months. The shape of perception index changes across CVAR models based on the break-even price and changes over time based on the variance of prices over the previous 24 months. The value of the normalized perception index at time t is multiplied by the GARCH(1,1) estimate for volatility at time t to calculate perceived volatility (*PerVol*) at time t.

Supplementary Table 1 Rank Test statistics for models chosen as most accurate (null hypothesis rank of Π is r [r cointegrating relations] as opposed to r+1)

r	Trace statistic for oil model	Trace statistic for gas model
0	110.7^{*}	166.0^{**}
1	77.6^{*}	88.1^{**}
2	45	39.1
3	21.6	13.6
4	4.9	4.5
5	1.7	0.3

Test statistics reject at the null hypothesis at the **1%, *5%, +10% level.

Supplementary Table 2 Test of stationarity (null hypotheses the variable is stationary)

	Oil model	Gas model
Rig	$\chi^2(2) = 24.3^{**}$	$\chi^2(2) = 45.3^{**}$
PerVol	$\chi^2(2) = 21.5^{**}$	$\chi^2(2) = 41.9^{**}$
Vol	$\chi^2(2) = 21.8^{**}$	$\chi^2(2) = 20.9^{**}$
Profit	$\chi^2(2) = 16.9^{**}$	$\chi^2(2) = 41.2^{**}$
Revenue	$\chi^2(2) = 26.6^{**}$	$\chi^2(2) = 43.7^{**}$
NRP	$\chi^2(2) = 22.1^{**}$	$\chi^2(2) = 42.6^{**}$

Test statistics reject at the null hypothesis at the **1%, *5%, +10% level.

Supplementary Table 3 Test of weak exogeneity (Null hypothesis is the variable is weakly exogenous and belongs in *w* in equation (7))

	Oil model	Gas model
Rig	$\chi^2(2) = 9.1^{*}$	$\chi^2(2) = 39.4^{**}$
PerVol	$\chi^2(2) = 4.0$	$\chi^2(2) = 0.2$
Vol	$\chi^2(2) = 4.2$	$\chi^2(2) = 11.9^{**}$
Profit	$\chi^2(2) = 6.6^{*}$	$\chi^2(2) = 29.1^{**}$
Revenue	$\chi^2(2) = 0.5$	$\chi^2(2) = 6.1^{*}$
NRP	$\chi^2(2) = 1.5$	$\chi^2(2) = 4.8$

Test statistics reject at the null hypothesis at the **1%, *5%, +10% level.

Supplementary Table 4 Analysis of residuals from the GARCH models

	Ljung-Box Q statistic	ARCH statistic	Jarque-Bera	Eliot *et al.*, (1996)
Gas0	0.608	0.271	47.18^{**}	0.38^{**}
Gas1	2.461	0.848	6.63*	0.42^{**}
Gas6	10.1^{**}	0.487	3.84	0.48^{**}
Gas12	4.153^{*}	0.589	2.56	0.39^{**}
Gas24	4.609	0.169	7.54^{*}	0.40^{**}
WTI0	8.114^{**}	0.081	0.42	0.88^{**}
WTI1	8.743^{**}	0.056	0.55	0.90^{**}
WTI6	10.848^{**}	0.133	3.01	1.05^{**}
WTI12	10.13^{**}	0.407	3.97	1.18^{**}
WTI24	9.413^{**}	0.366	6.08^{*}	1.19^{**}

Test statistics reject at the null hypothesis at the **1%, *5%, $^{+}$10% level.

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