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AN EQUILIBRIUM MODEL OF THE OIL INDUSTRY

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ABSTRACT

We use a new micro data set to compile some key facts about the oil market and estimate a structural industry equilibrium model that is consistent with these facts. We find that demand and supply shocks contribute equally to the volatility of oil prices but that the volatility of investment by oil firms is driven mostly by demand shocks. Our model predicts that the advent of fracking will eventually result in a large reduction in oil price volatility.

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1 Introduction

The interaction between oil markets and the world economy has been a subject of longstanding interest in macroeconomics. In this paper, we study this interaction using a stochastic equilibrium model of the oil industry. Our analysis relies heavily on a new micro data set that contains information on production, reserves, operational costs, and investment for all oil fields in the world.

We use these data to guide the construction of our model in three ways. First, we compile a set of facts about oil markets that a successful model should be consistent with. Second, we produce micro estimates of two key model parameters: the average lag between investment and production and the elasticity of extraction costs with respect to production. Third, we use the generalized method of moments (GMM) to estimate the remaining model parameters, targeting a set of second moments for oil-related variables.

There is substantial heterogeneity across oil firms along various dimensions. We find two sources of heterogeneity that are particularly important. The first is the different behavior of firms that are part of the Organization of the Petroleum Exporting Countries (OPEC) and those that are not. The second is the difference between hydraulic fracturing (fracking) and conventional oil production. Our benchmark model features heterogeneity only in the OPEC/non-OPEC dimension. Our extended model includes firms that use conventional oil production methods as well as fracking.

We use our model to measure the importance of demand and supply shocks in driving prices, production, and investment. We find that supply and demand shocks contribute equally to the volatility of oil prices but that investment in the oil industry is driven mostly by demand shocks. The reason for this pattern is twofold. There is a long lag between investment and production and supply shocks are short-lived relative to demand shocks. So, investment responds much more to demand than to supply shocks. We also find that the volatility of OPEC production firms is driven primarily by supply shocks that disrupt the ability of these firms to extract oil. In contrast, both demand

and supply shocks are important in explaining the volatility of non-OPEC production.

As discussed above, our data allows us to document two key differences between hydraulic fracturing (fracking) and conventional oil production. First, it is less costly for fracking firms to adjust their level of production in the short run, so these firms are more responsive to changes in prices. Second, the lag between investment and production in much shorter in fracking operations than in conventional oil production.

We introduce fracking firms into our model to study their impact on the dynamics of the oil market. We find that their presence leads to a large decline in the volatility of oil prices. The reason is simple: these firms are more nimble in adjusting production levels from existing fields and in starting production in new fields, so they can respond more quickly to price increases.

In Section 2 we review the following six facts about the oil market. First, the average rate of change of inflation-adjusted oil prices is not significantly different from zero. Second, oil prices are very volatile, much more volatile than returns to the stock market or exchange rates. Third, investment in the oil industry is very volatile, roughly seven times more volatile than U.S. aggregate investment. Fourth, investment in the oil industry shows a strong, positive correlation with the inflation-adjusted price of oil. Fifth, there is a low short-run elasticity of the supply of oil from individual oil fields with respect to price. Sixth, production by OPEC firms is more volatile and less correlated with oil prices than production by non-OPEC production firms.

We describe our model in Section 3. Section 4 is devoted to estimating model parameters using both micro data and moments of key aggregate variables for the oil industry. The estimated version of our model has four main features. First, demand is relatively inelastic. Second, supply is elastic in the long run because firms can invest in the discovery of new oil fields.[1] Third, supply is inelastic in the short run. This

[1]While the amount of oil is ultimately finite, we can think about this investment process as including new ways of extracting oil as well as the development of oil substitutes, as in Adao et al. (2012). There has been a large expansion of oil reserves during our sample period. According to the U.S. Energy Information Administration, proved oil reserves measured in years of production have increased from

property results from several model features: there is a lag between investment and production, there are convex costs of adjusting extraction rates, and there are point-in-time decreasing returns to oil investment. Fourth, there are shocks to demand, e.g., faster growth in China, and to the supply of OPEC firms, e.g., the Iran-Iraq war.

This paper is most closely related to work on models of the response of oil prices and production to fluctuations in the world economy. Examples of this work include Backus and Crucini (2000), Kilian (2009), Bodenstein et al. (2011), and Lippi and Nobili (2012).[2] Our paper is also related to the literature that uses VARs to estimates the importance of demand and supply shocks on the volatility of oil prices (see the comprehensive surveys by Hamilton (2005) and Kilian (2008) and the references therein). Our approach, which is based on a structural model, is complementary to that adopted in this literature. Finally, our paper is related to a new, emerging literature that uses micro data to shed new light on key aspects of the oil industry (see, e.g., Kellogg (2014), Arezki et al. (2016), and Anderson et al. (2017)).

2 Key facts about the oil market

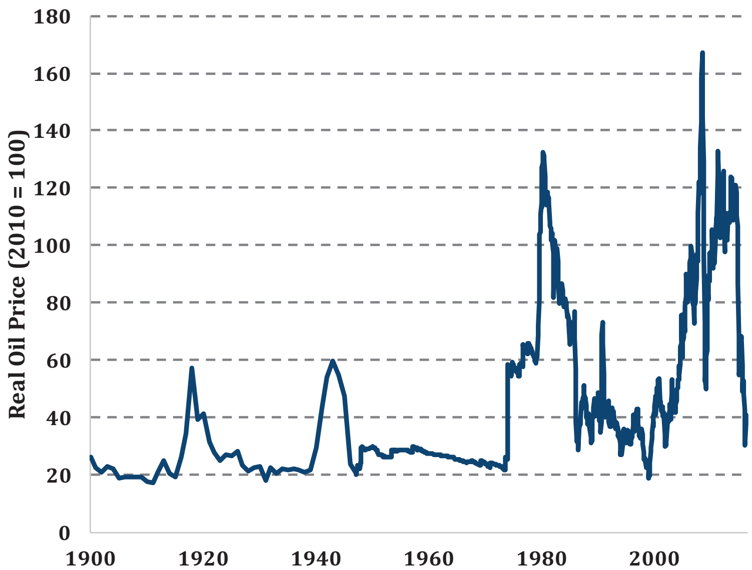
In this section we review six facts about the oil market. Most of our analysis relies on a proprietary data set compiled by Rystad Energy that includes information on reserves, production, investment, and operational costs for the universe of oil fields. The data contains information about roughly 14,000 oil fields operated by 3,200 companies.

We focus our analysis on the period from 1970 to 2015. Until 1972, U.S. regulatory agencies sought to keep U.S. oil prices stable by setting production targets. This period of stability ended once the U.S. ceased to be a net oil exporter (see Hamilton (1983) and Kilian (2014)).

roughly 30 years in 1980 to 52 years in 2015.

[2]Earlier work on the impact of oil shocks on the economy generally treats oil prices as exogenous (see, e.g., Kim and Loungani (1992), Rotemberg and Woodford (1996), and Finn (2000)).

Figure 1: Real price of oil



There is no significant time trend in real oil prices Figure 1 plots the price of an oil barrel expressed in dollars and deflated by the U.S. consumer price index from 1900 to 2015.[3] The average annual growth rate in the real price of oil during this period is not statistically different from zero. For the period from 1900 to 2015 this average is 0.01 with a standard error of 0.21.[4] For the period from 1970 to 2015 this average is 0.02 with a standard error of 0.27.

Oil prices are very volatile Figure 1 shows that oil prices are quite volatile since the early 1970s. From 1970 to 2015, the volatility of oil prices is higher than that of returns to the stock market or exchange rates. The standard deviation of the annual percentage change in oil prices is 0.28 for nominal prices and 0.27 for real prices. In

[3]Between 1900 and 1947, our source for the price of oil is Harvey et al. (2010). After 1947, we use the price of West Texas Intermediate.

[4]The property that average growth rates in real prices estimated over long time periods are close to zero is shared by many other commodities (Deaton and Laroque (1992), Harvey et al. (2010) and Chari and Christiano (2014)).

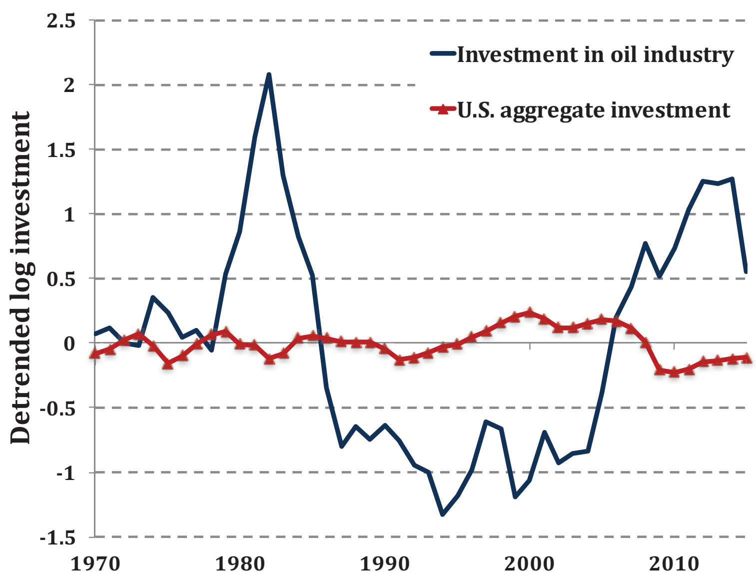
contrast, the standard deviation of nominal returns to the S&P 500 is 16 percent and the standard deviation of changes in exchange rates is 10 percent.

These first two facts were aptly summarized by Deaton (1999) with the phrase "What commodity prices lack in trend, they make up for in variance."

Investment in the oil industry is very volatile The annual standard deviation of the growth rate of real world investment in the oil industry is 0.36 for the period 1970-2015. To put this number in perspective, this measure of volatility is 0.10 for U.S. manufacturing and 0.07 for U.S. aggregate investment.[5]

Figure 2 illustrates the high volatility of investment in the oil industry. This figure plots the linearly-detrended logarithm of two series: real word-wide investment in the oil industry and real aggregate investment in the U.S.

Figure 2: Detrended investment in the oil industry



[5]The only major U.S. manufacturing sector with volatility of investment similar to the oil industry in the period 1970-2015 is Motor vehicle manufacturing, a sector that has struggled to compete with foreign manufacturers and had to be bailed out by the Federal government in 2009.

Investment in the oil industry is positively correlated with oil prices Figure 3 plots the logarithm of the inflation-adjusted price of oil and the logarithm of inflation-adjusted world investment in the oil industry. The correlation between the growth rate of the price of oil and the growth rate of investment is 0.51.

Figure 3: Oil prices and oil investment

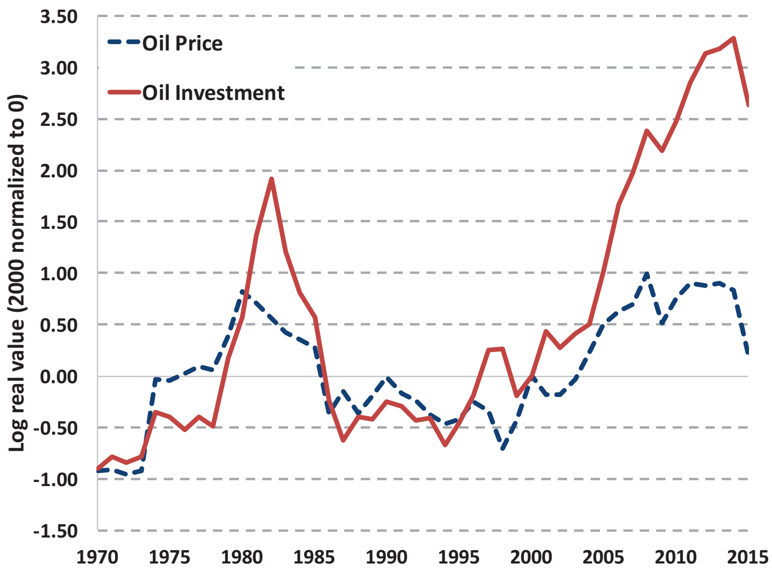


Table 1 reports the correlation between the growth rate of real investment and the growth rate of the real oil prices for each of the top twenty firms in the oil industry in descending order.[6] We see that the correlation is high for every major oil firm with the exception of Iran's NIOC, Total, and Eni, which show a correlation near zero.

The short-run elasticity of oil supply is very low Oil producers can respond to an increase in the market price of oil in two ways. The first is to produce more oil from oil fields in operation by increasing the extraction rate. The second is to increase the number of oil fields in operation. We show that the short-run elasticity of the extraction

[6]Firms are ranked according to their total oil production in 2015.

Table 1: Investment and price correlation for top 20 firms

Firm	Headquarters	OPEC	$corr(\Delta i, \Delta p)$
Saudi Aramco	Saudi Arabia	✓	0.31
Rosneft	Russia	✗	0.34
PetroChina	China	✗	0.36
Kuwait Petroleum Corp (KPC)	Kuwait	✓	0.3
NIOC (Iran)	Iran	✓	0.06
Pemex	Mexico	✗	0.27
ExxonMobil	United States	✗	0.35
Lukoil	Russia	✗	0.41
Petrobras	Brazil	✗	0.3
PDVSA	Venezuela	✓	0.28
Abu Dhabi NOC	Abu Dhabi	✓	0.14
Chevron	United States	✗	0.43
Shell	Netherlands	✗	0.34
BP	United Kingdom	✗	0.35
Surgutneftegas	Russia	✗	0.26
South Oil Company (Iraq NOC)	Iraq	✓	0.19
Total	France	✗	0.04
CNOOC	China	✗	0.4
Statoil	Norway	✗	0.34
Eni	Italy	✗	0.04

rate to an exogenous change in the price of oil is positive but small.[7] We also show that the elasticity of response of the number of oil fields in operation to an exogenous change in the price of oil is not statistically different from zero.

Table 2 reports panel-data estimates of the elasticity of the extraction rate (the ratio of production to reserves) for a given oil field with respect to real oil prices.[8] These estimates suggest that a rise in oil prices leads to a very small increase in the supply of oil from a given oil field.[9]

Our estimates are obtained by running various versions of the following regression:

$$\ln \theta_{it} = \alpha_i + \beta \ln p_t + \gamma X_{it} + \varepsilon_{it},$$

where θ_{it} denotes the extraction rate of oil field i at time t, p_t is the real price of oil, and X_{it} represents other controls.[10] These controls include a time trend, an oil-field fixed effect, and a fixed effect for year of operation to control for the life cycle of an oil field.[11]

Specification 1 in Table 2 is a simple OLS regression. The estimated slope coefficient that results from this regression can be biased if there is technical progress that lowers the cost of extraction, raising θ_{it}, increasing the supply of oil, and lowering p_t. To address this problem, we instrument the price of oil with our forecast of the cyclical component of world GDP. This forecast is correlated with aggregate demand and unaffected by aggregate cost shocks.

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[7] Anderson et al. (2017) estimate this elasticity to be close to zero. The difference between our results and theirs is likely to reflect differences in data frequency: their data is monthly while ours is annual.

[8] In our data, reserves are proven reserves, which measure the total amount of oil that can be produced from a given field. Reserves do not change in response to changes in oil prices, so there is no mechanical impact of oil prices on extraction rates.

[9] An oil field generally contains many oil rigs. Production increases can result from the intensive margin (higher production from existing oil rigs) or from the extensive margin (drilling new oil rigs). Anderson et al. (2017) use a sample of Texas oil rigs to show that the elasticity of the intensive margin is close to zero, so production increases result from the extensive margin.

[10] Our data includes all oil fields with a positive extraction rate for the period 1971-2015 excluding the last year of operation.

[11] See Arezki et al. (2016) and Anderson et al. (2017) for discussions of this life cycle.

Table 2: Price elasticity of extraction rates

Variable	(1)	(2)	(3)	(4)	(5)
ln(price)	0.09***	0.12***	0.16***	0.17***	0.16***
	(0.009)	(0.012)	(0.017)	(0.023)	(0.013)
ln(price) $\times \mathbb{1}_{\text{OPEC}}$			−0.2***	−0.19***	
			(0.069)	(0.069)	
ln(price) $\times \mathbb{1}_{\text{Big Firm}}$				−0.06	
				(0.054)	
ln(price) $\times \mathbb{1}_{\lvert\Delta \ln(p)\rvert>0.1}$					−0.17***
					(0.009)
Oil field FE	✓	✓	✓	✓	✓
Operation year FE	✓	✓	✓	✓	✓
Year trend	✓	✓	✓	✓	✓
IV	✗	✓	✓	✓	✓
Clusters (oil fields)	12,187		11,479		
Observations	173,742		173,034		

Oil fields with positive extraction in 1971-2015, excluding last year of operation. Standard errors in parenthesis. Instrument for price using the forecast of the cyclical component of world GDP. F-stat > 1000 in (2)-(5). $(***)$ - significant at a 1% level.

Our forecast of the cyclical component of world GDP is obtained as follows. We HP-filter the series for world real GDP and estimate an AR process for the resulting cyclical component. Choosing the number of lags using the Akaike information criterion resulted in an AR(2) process.

Specifications 2-5 use this instrument. Our benchmark specification is regression 2 which yields an estimate for β equal to 0.12. The following calculation is useful for evaluating the magnitude of this elasticity. The average extraction rate in our sample is 2.8 percent. A one standard deviation (13.5 percent) increase in price raises the extraction rate from 2.8 percent to 2.85 percent, resulting only in a 1.8 percent increase in production.

Specification 3 includes the product of the logarithm of the price and an OPEC dummy. We see that OPEC firms respond less to changes in prices than non-OPEC firms. The point estimate for the response of OPEC to oil price shocks is negative (-0.04) and insignificant (P-value = 0.48).

Specification 4 includes also an interaction term that is the product of logarithm of price and a dummy for firm size. This dummy is equal to one for firms that produced more than 0.5 billion barrels of oil in 2015. Total production in 2015 was approximately 27.5 billion barrels of oil so that each large firm according to our definition has at least a 1.8 percent market share. The idea is to investigate whether large firms behave differently from small firms. We find no evidence of a firm-size effect.

Specification 5 includes an interaction term that is the product of logarithm of price and a dummy for price changes that are larger than 10 percent in absolute value. The idea is to investigate whether firms react more to large oil price changes than to small price changes. We find that the coefficient on the interaction term is negative (-0.17) and statistically significant. This finding is consistent with the presence of convex adjustment costs in the extraction rate, so that the elasticity of response is higher for small price changes than for large price changes.

These results remain robust when we extend the sample to start in 1900 (see Table 15 in the appendix) with two exceptions. In the long sample, the coefficients on large firms and large price movements are both negative and statistically significant.

Table 3 reports our time-series estimates of the elasticity of the number of oil fields in operation with respect to real oil prices. Specification 1 is a simple OLS regression where the dependent variable is the logarithm of oil fields in operation world wide and the independent variable is the logarithm of real oil prices. Specification 2 uses our forecast of the cyclical component of world GDP as an instrument for the logarithm of real oil prices. Specifications three and four report results for non-OPEC fields and OPEC fields, respectively. All four specifications yield elasticity estimates that are statistically insignificant. We also find an insignificant elasticity when we extend our

Table 3: Price elasticity of oil fields in operation

Variable	**(1)**	**(2)**	**(3)**	**(4)**
ln(price)	−0.05 (0.06)	−0.02 (0.08)	−0.01 (0.03)	0 (0.06)
Year trend	✓	✓	✓	✓
IV	✗	✓	✓	✓
Dep. variable	All fields	All fields	Non-OPEC fields	OPEC fields
Observations	45	45	45	45

Newey-West standard errors with 5 years lag in parenthesis.

sample to start in 1900 (see Table 14 in the appendix).

Taken together, these results suggest that the number of oil fields in operation does not respond in the short-run to changes in oil prices.

OPEC and non-OPEC firms behave differently Table 4 shows that OPEC and non-OPEC firms differ in the volatility and persistence of production and investment, as well as in the correlation of these variables with real oil prices. The production of OPEC firms is more volatile and less persistent than that of non-OPEC firms. In addition, the correlation between investment and prices is higher for non-OPEC firms than for OPEC firms. These patterns are likely to result from supply shock to OPEC firms, such as the disruptions in oil markets associated with the Iranian revolution and the Iran-Iraq war.

Table 4: Correlation table of OPEC and non-OPEC production and investment

	Δp	Δi_n	Δi_o	Δq_n	Δq_o	*std*	*Acorr*
Δp	1.00					0.27	-0.03
Δi_n	0.56	1.00				0.19	0.12†
Δi_o	0.36	0.67	1.00			0.19	0.31
Δq_n	0.03†	0.09†	−0.03†	1.00		0.02	0.64
Δq_o	0.03†	0.02†	−0.23†	-0.14†	1.00	0.07	0.21†

† - not significant at a 5% level. See table 7 for standard errors.

3 An industry-equilibrium model

In this section we describe our equilibrium model of the oil industry. Our goal is to propose a parsimonious model that is consistent with the facts described in Section 2.

We assume that the world demand for oil is given by

$$P_t = \exp(d_t) Q_t^{-1/\varepsilon},$$

where P_t is the real price of oil, Q_t is the quantity consumed, and ε is the price elasticity of the demand for oil. The variable d_t is a stochastic demand shock that follows an AR(2) process in logarithms

$$\ln(d_t) = \rho_1^d \ln d_{t-1} + \rho_2^d \ln d_{t-2} + e_t^d.$$

We choose this AR(2) specification so that demand shocks can follow a hump-shaped pattern. This pattern allows an initial shock to contain news about a future rise in the demand for oil associated, for example, with faster growth in China.

Non-OPEC firms There is a continuum of measure one of non-OPEC firms. These firms maximize their value (V^N) which is given by

$$V^N = E_0 \sum_{t=0}^{\infty} \beta^t \left[P_t \theta_t^N K_t^N - I_t^N - \psi \left(\theta_t^N \right)^{\eta} K_t^N \right]. \tag{1}$$

Here, I_t^N denotes investment, θ_t^N the extraction rate (the ratio of production to reserves), and K_t^N oil reserves. The term $\psi \left(\theta_t^N\right)^\eta K_t^N$ represents the costs of extracting oil. We assume extraction costs are linear in reserves so that aggregate production and aggregate extraction costs are invariant to the distribution of oil reserves across firms. This formulation allows us to use a representative firm to study production and investment decisions. We assume that $\eta > 1$, so that these costs are convex, and that the time $t+1$ extraction rate is chosen at time t.

We adopt a parsimonious way of modeling lags in investment by introducing *oil in process*, which we denote by X_t. The timing of the realization of shocks and firm decisions is as follows. In the beginning of the period, the demand and supply shocks are realized, a fraction λ of the oil in process materializes into new oil reserves, and production occurs according to the predetermined extraction rate. At the end of the period, the firm chooses its investment and its extraction rate for the next period. The law of motion for oil in process is as follows:

$$X_{t+1}^N = (1-\lambda)X_t^N + \left(I_t^N\right)^\alpha \left(L^N\right)^{1-\alpha}. \tag{2}$$

Investment adds to the existing oil in process, but only a fraction λ of the oil in process materializes into oil reserves in every period. Investment requires land (L^N) and exhibits point-in-time decreasing returns ($\alpha < 1$). Without this feature, investment would be extremely volatile, rising sharply when prices are high and falling deeply when prices are low.

One interpretation of equation (2) is as follows. Suppose each firm searches for oil on a continuum of oil fields containing X_t^N barrels of oil uniformly distributed across fields. The probability of finding oil is independent across oil fields and equal to λ. By the law of large numbers, each firm finds λX_t^N oil reserves at time t. We pursue this interpretation when we estimate λ using our micro data.

Oil reserves evolve as follows:

$$K_{t+1}^N = (1-\theta_t^N)K_t^N + \lambda X_{t+1}^N. \tag{3}$$

Reserves fall with oil production ($\theta_t^N K_t^N$) and rise as oil in process materializes into new reserves (λX_{t+1}^N).

The notion of oil in process embodied in equations (2) and (3) is a tractable way of introducing time-to-build in investment that might be useful in other problems. This formulation allows us to introduce a lag between investment and production by adding only one state variable. The parameter λ allows us to smoothly vary the length of the lag.[12]

The problem of the representative non-OPEC firm is to choose the stochastic sequences for I_t^N, θ_{t+1}^N, K_{t+1}^N, and X_{t+1}^N that maximize its value defined in equation (1), subject to constraints (2) and (3).

The first-order conditions for θ_{t+1}^N is

$$E_t P_{t+1} = \psi\eta \left(\theta_{t+1}^N\right)^{\eta-1} + E_t \mu_{t+1}^N, \tag{4}$$

where μ_t^N is the Lagrange multiplier corresponding to equation (3). The extraction rate at time $t+1$ is chosen at time t so as to equate the expected oil price to the sum of the marginal cost of extraction, $\psi\eta \left(\theta_{t+1}^N\right)^{\eta-1}$, and the expected value of a barrel of oil reserves at the end of time $t+1$, $E_t \mu_{t+1}^N$.

The first-order condition for K_{t+1} is

$$\mu_t^N = E_t \beta \left\{ \left[P_{t+1}\theta_{t+1}^N - \psi \left(\theta_{t+1}^N\right)^{\eta} \right] + (1-\theta_{t+1}^N)\mu_{t+1}^N \right\}. \tag{5}$$

For a given value of θ_{t+1}^N, each additional barrel of oil reserves results in additional revenue equal to $P_{t+1}\theta_{t+1}^N$ and increases extraction costs by $\psi \left(\theta_{t+1}^N\right)^{\eta}$. A fraction $1-\theta_{t+1}^N$ of the barrel of reserves remains in the ground and has a value of $\beta E_t \mu_{t+1}^N$.

The first-order condition for X_{t+1} is

$$\nu_t^N = \lambda \mu_t^N + \beta(1-\lambda) E_t \nu_{t+1}^N, \tag{6}$$

[12]See Rouwenhorst (1991) for a discussion of the large state space and complex dynamics associated with time-to-build formulations.

where ν_t^N is the Lagrange multiplier corresponding to equation (2). The value of increasing oil in process by one unit, ν_t^N, has two components. A fraction λ materializes into oil reserves and has a value μ_t^N. A fraction $1-\lambda$ remains as oil in process and has an expected value $\beta E_t \nu_{t+1}^N$.

The first order condition for I_t is

$$1 = \alpha \left(I_t^N\right)^{\alpha-1} \left(L^N\right)^{1-\alpha} \nu_t^N. \tag{7}$$

This equation equates the cost of investment (one unit of output) to the marginal product of investment in generating oil in process, $\alpha \left(I_t^N\right)^{\alpha-1} \left(L^N\right)^{1-\alpha}$, evaluated at the value of oil in process, ν_t^N.

OPEC firms There is a continuum of measure one of OPEC firms. The problem for these firms is to maximize their value (V^O) which is given by

$$V^O = E_0 \sum_{t=0}^{\infty} \beta^t \left(P_t e^{-u_t} \theta_t^O K_t^O - I_t^O - \psi \left(\theta_t^O\right)^\eta K_t^O\right). \tag{8}$$

The key difference between OPEC and non-OPEC firms is that the former are subject to a supply shock, u_t.[13] When this shock occurs, production falls for a given level of the extraction rate. We assume that supply shocks follow an AR(2) process:

$$\ln u_t = \rho_1^u \ln u_{t-1} + \rho_2^u \ln u_{t-2} + e_t^u,$$

and that innovations to demand (e_t^d) and supply (e_t^u) are uncorrelated. The laws of motion for oil in process and reserves are given by

$$X_{t+1}^O = (1-\lambda) X_t^O + \left(I_t^O\right)^\alpha \left(L^O\right)^{1-\alpha}, \tag{9}$$

$$K_{t+1}^O = (1 - e^{-u_t}\theta_t^O) K_t^O + \lambda X_{t+1}^O. \tag{10}$$

[13] To simplify, we abstract from supply shocks to non-OPEC producers. While there are supply shocks to non-OPEC producers (e.g., Canadian wildfires and Gulf of Mexico hurricanes), they seem small relative to the supply shocks to OPEC producers. This view is consistent with the higher volatility of production in OPEC relative to non-OPEC.

The problem of the representative OPEC firm is to choose the stochastic sequences for I_t^O, θ_{t+1}^O, K_{t+1}^O, and X_{t+1}^O that maximize its value defined in equation (8), subject to constraints (9) and (10).

The first-order conditions for the problem of OPEC firms are as follows:

$$\begin{aligned}
&E_t\left(P_{t+1}e^{-u_{t+1}}\right) = \psi\eta\left(\theta_{t+1}^O\right)^{\eta-1} + E_t\left(\mu_{t+1}^O e^{-u_{t+1}}\right), \\
&\mu_t^O = E_t\beta\left\{\left[P_{t+1}e^{-u_{t+1}}\theta_{t+1}^O - \psi\left(\theta_{t+1}^O\right)^{\eta}\right] + (1-e^{-u_{t+1}}\theta_{t+1}^O)\mu_{t+1}^O\right\}, \\
&\nu_t^O = \lambda\mu_t^O + \beta(1-\lambda)E_t\nu_{t+1}^O, \\
&1 = \alpha\left(I_t^O\right)^{\alpha-1}\left(L^O\right)^{1-\alpha}\nu_t^P.
\end{aligned}$$

These first-order conditions are similar to those for non-OPEC firms. The key difference is that production of OPEC firms is scaled by the supply shock $e^{-u_{t+1}}$.

Equilibrium In equilibrium, P_t is a function of demand and supply shocks, the aggregate level of reserves in OPEC ($\mathbf{K}_t^O$) and non-OPEC ($\mathbf{K}_t^N$), and the predetermined aggregate levels of extraction rates in OPEC ($\boldsymbol{\theta}_t^O$) and non-OPEC ($\boldsymbol{\theta}_t^N$):

$$P_t = p(d_t, u_t, \mathbf{K}_t^O, \mathbf{K}_t^N, \boldsymbol{\theta}_t^O, \boldsymbol{\theta}_t^N). \tag{11}$$

Firms maximize their value subject to the laws of motion for reserves and oil in process. Each firm takes the law of motion for the aggregate levels of reserves, extraction rates, and oil in process as given and so the price process is exogenous to each individual firm. These laws of motion for the aggregate variables depend on the six aggregate state variables included in equation (11) and the aggregate levels of oil in process in OPEC ($\mathbf{X}_t^O$) and non-OPEC ($\mathbf{X}_t^N$).

The oil market clears, i.e., total oil production equals total oil demand:

$$\boldsymbol{\theta}_t^N\mathbf{K}_t^N + e^{-u_t}\boldsymbol{\theta}_t^O\mathbf{K}_t^O = Q_t.$$

Since there is a continuum of measure one of identical firms within the two groups, OPEC and non-OPEC. In equilibrium, the values of aggregate variables for each group coincide with the values of the corresponding variables for the representative firm in each group.

The Hotelling rule The classic Hotelling (1931) rule emerges as a particular case of our model in which there are no OPEC firms, $\lambda = 0$, and $\eta = 1$. When $\lambda = 0$, investment does not result in more oil reserves, so oil is an exhaustible resource. Equation (6) implies that in this case the value of oil in process is zero: $\nu_t^N = 0$. Combining equations (4) and (5) we obtain

$$E_t P_{t+1} - \psi = \beta E_t (P_{t+2} - \psi).$$

This equation is the Hotelling rule: the price of oil minus the marginal cost of production is expected to rise at the rate of interest in order to make oil producers indifferent between extracting oil at $t+1$ and at $t+2$.

For the general case where $\lambda \geq 0$ and $\eta \geq 1$, the marginal cost of production is $\eta\psi\theta_t^{\eta-1}$ and the difference between the price of oil and the marginal cost of production is given by

$$E_t \left(P_{t+1} - \eta\psi\theta_{t+1}^{\eta-1} \right) = \beta E_t \left(P_{t+2} - \eta\psi\theta_{t+2}^{\eta-1} \right) + \beta E_t \left(\eta - 1 \right) \psi\theta_{t+2}^{\eta}.$$

The term $\beta E_t (\eta - 1) \psi\theta_{t+2}^{\eta}$ represents the marginal fall in production costs at time $t+2$ from having an additional barrel of oil reserves. When $\eta = 1$, this term is zero and we recover the Hotelling rule.

When $\lambda = 0$ (more oil cannot be found), there is no steady state in which P_t and θ_t are constant.[14] When the extraction rate is constant, production falls over time and, since demand is downward sloping, the price of oil rises over time. When the price is constant, production must also be constant and so the extraction rate must rise.

In our model $\lambda > 0$ and $\eta > 1$. Because it is feasible to find more oil, there is a steady state in which both P_t and θ_t are constant. Oil reserves are constant and so

[14] When $\lambda = 0$ and $\eta > 1$ our economy resembles the model proposed by Anderson et al. (2017). Changes in the extraction rate in our model play a similar role to drilling new wells in their model.

the quantity produced is also constant. In the steady state, the marginal decline in production costs from an additional barrel of oil is such that the difference between price and marginal cost remains constant:

$$\beta\left(\eta-1\right)\psi\theta^{\eta}=\left(1-\beta\right)\left(P-\eta\psi\theta^{\eta-1}\right).$$

4 Model solution and estimation

We solve the model using a second-order approximation around its non-stochastic steady state. In the non-stochastic steady state the ratio of production by OPEC and non-OPEC firms is equal to the ratio of the land available to each of the two groups:

$$\frac{L^{O}}{L^{N}}=\frac{\theta^{O}K^{O}}{\theta^{N}K^{N}}.$$

We calibrate some key parameters using our micro data set as well as information about the cost of capital in the oil industry. We estimate the remaining parameters using GMM.

We choose the ratio L^{O}/L^{N}so that in the steady state the ratio of OPEC to non-OPEC production is equal to the average of this ratio in our data (0.82). We calibrate the total amount of land $(L^{O}+L^{N})$ so that the steady-state extraction rate coincides with the average extraction rate in our data (2.8 percent).

The parameter ψ matters only for the level of oil prices, so we normalize it to one. We set $1/\beta-1$, the real discount rate, to 8 percent which is the real cost of capital estimated by Damodaran (2017) for the oil industry.

4.1 Estimating λ and η with micro data

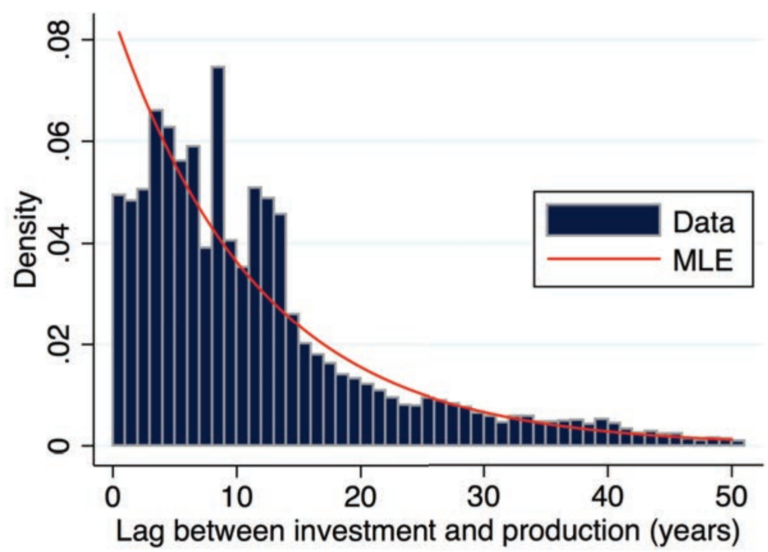
To estimate λ, we compute the lag between the first year of investment and first year of production (T_i) for every oil field in our data set. If the arrival of production occurs according to a Poisson process, the lag between investment and production follows a geometric distribution with mean λ. The maximum likelihood estimator for λ is:

$$\hat{\lambda} = \frac{N}{\sum_{i=1}^{N} T_i} = 0.085,$$

where N denotes the number of oil fields.

This estimate implies that the average lag between investment and production is 12 years. Figure 4 shows the empirical distribution of this lag together with the implied geometric distribution for our estimate of $\hat{\lambda}$.[15]

Figure 4: Empirical distribution of lags between investment and production



We also use our micro data to estimate η, the parameter that controls the convexity of the extraction costs. We run the following regression:

$$\ln \left[\frac{C(\theta_{it}, K_{it})}{K_{it}} \right] = \gamma_i + \eta \ln(\theta_{it}) + \varepsilon_{it},$$

[15]Our estimate of the average production lag is higher than that reported in Arezki et al. (2016). This difference occurs because we estimate the lag between initial investment (which includes seismic analysis and drilling wells to discover and delineate oil fields) and production. Arezki et al. (2016) estimate the lag between oil discovery and production, which is shorter.

where $C(\theta_{it}, K_{it})$ denotes extraction costs. The potential presence of cost shocks, either field specific or aggregate, creates an endogeneity problem. Suppose it becomes more costly to extract oil, so that firms reduce their extraction rates. This correlation between the cost and the rate of extraction biases downward in our estimate for η. To address this problem, we instrument the extraction rate with our forecast of the cyclical component of world GDP. This forecast is correlated with aggregate demand and unaffected by field-specific cost shocks.

Our data includes all oil fields with positive extraction rates between 1971 and 2015. We exclude the last year of oil field operation since the data for this year includes the costs of shutting down the field, which are not related to the rate of extraction.

Table 5 contains our slope estimates. Specifications 1 through 4 include fixed effects for oil field and operation year. Specification 1 includes all the oil fields in our sample. Specification 2 includes only non-OPEC firms. Specification 3 includes only OPEC firms. While our instrument is independent of oil-field-specific cost shocks, it may be correlated with aggregate supply shocks. The Iran-Iraq war, for example, may have caused a slowdown in world GDP at the same time as interrupting the supply of oil by the two countries. As a result, the point estimate is negative and statistically insignificant. We use specification 2 as our benchmark and set η equal to the point estimate (9.3). The fact that $\eta > 1$ is consistent with the fact that the elasticity of response of production to prices is higher for small price increases than for large price increases (see regression 3 in Table 2).

GMM estimation We estimate ϵ, α, the parameters of the AR(2) processes for demand and supply shocks, together with the variance of the two shocks using GMM. Table 6 reports our results. Our estimate for ϵ is 0.135 with a standard error of 0.015. This point estimate implies that demand is very inelastic. A 1 percent increase in production reduces the price by 7.4 percent.

Table 5: Extraction rate adjustment costs regression

Variable	**(1)**	**(2)**	**(3)**
ln(extraction)	11.49***	9.30***	−36.65
	(1.60)	(1.14)	(41.06)
Oil field FE	✓	✓	✓
Operation year FE	✓	✓	✓
Sample	All	Non-OPEC	OPEC
IV	✓	✓	✓
1^{st} stage F-stat	43	53	1
Clusters (oil fields)	11,527	9,969	1,558
Observations	174,339	146,879	27,460

To see why demand needs to be inelastic, it is useful to write the demand function:

$$\ln P_t = d_t - \frac{1}{\epsilon} \ln q_t.$$

The model embeds two mechanisms that generate price volatility. The first mechanism is a low value of ϵ that makes low production volatility consistent with high price volatility. The second mechanism is volatile demand shocks. Since oil prices are highly persistent (changes in prices are roughly i.i.d.), demand shocks must also be highly persistent. Volatile, persistent demand shocks lead to high volatility in investment and production. The observed volatility of investment and production help determine the importance of the two channels and therefore identify ϵ.

Table 6 shows that the standard errors associated with our parameter estimates are generally small. The only parameter that is imprecisely estimated is alpha. This imprecision results from the small impact of local changes in the value of α on the moments implied by the model. Our point estimate of α is close to zero. However, it is important that α be strictly positive since, when $\alpha = 0$, the model has the counterfactual implication that there should be no investment in the oil industry.

Table 6: Estimated parameters

Parameter	**Estimate**	(s.e.)
ϵ	0.135	(0.015)
α	3×10^{-6}	(0.978)
ρ_1^d	1.761	(0.075)
ρ_2^d	-0.775	(0.073)
ρ_1^u	1.428	(0.15)
ρ_2^u	-0.51	(0.11)
$var(e_t^d)$	0.02	(0.007)
$var(e_t^u)$	0.002	(0.001)

Table 7 compares the estimated moments targeted by our GMM procedure with the population moments implied by the model. We see that the fit of the model is good with most of the model population moments inside the 95 percent confidence interval of data moments. One exception is the correlation between changes in prices and change in quantities for OPEC firms which is negative in the model and close to zero in the data.

One interesting property of the model is that it is consistent with the high correlation between prices and investment. In the literature on the cattle and hog cycles (e.g., Ezekiel (1938) and Nerlove (1958)) this positive correlation is often interpreted as suggesting that expectations have a backward-looking component. Investment rises when prices are high, sowing the seeds of a future fall in prices. In our model, the high correlation between the price of oil and investment results from the rational response of forward-looking firms. A positive demand shock raises the price of oil above its steady state level. As a result it is profitable to invest in oil to expand production and take advantage of the high oil prices. This supply expansion brings the price back to its steady state level.

Another interesting property is that both in the data and in the model changes in the price of oil are close to being i.i.d. So, in the short run, the stochastic process for oil prices is well approximated by a random walk. A related result is that the volatility

Table 7: Data and model moments

	Moment	**Data**	(s.e.)	**Model**
(1)	std(Δp_t)	0.273	(0.028)	0.227
(2)	std(Δi_t^n)	0.192	(0.24)	0.213
(3)	std(Δi_t^o)	0.193	(0.27)	0.211
(4)	std(Δq_t^n)	0.022	(0.003)	0.025
(5)	std(Δq_t^o)	0.069	(0.011)	0.054
(6)	corr(Δp_t, Δi_t^n)	0.557	(0.147)	0.709
(7)	corr(Δp_t, Δi_t^o)	0.362	(0.109)	0.657
(8)	corr(Δp_t, Δq_t^n)	0.031	(0.069)	0.049
(9)	corr(Δp_t, Δq_t^o)	0.030	(0.122)	-0.572
(10)	corr(Δi_t^n, Δi_t^o)	0.673	(0.096)	0.997
(11)	corr(Δi_t^n, Δq_t^n)	0.087	(0.094)	-0.001
(12)	corr(Δi_t^n, Δq_t^o)	0.023	(0.112)	-0.103
(13)	corr(Δi_t^o, Δq_t^n)	-0.034	(0.145)	0.003
(14)	corr(Δi_t^o, Δq_t^o)	-0.226	(0.153)	-0.036
(15)	corr(Δq_t^n, Δq_t^o)	-0.141	(0.125)	0.014
(16)	corr(Δp_t, Δp_{t-1})	-0.027	(0.088)	-0.018
(17)	corr(Δi_t^n, Δi_{t-1}^n)	0.119	(0.135)	0.008
(18)	corr(Δi_t^o, Δi_{t-1}^o)	0.311	(0.096)	0.009
(19)	corr(Δq_t^n, Δq_{t-1}^n)	0.643	(0.113)	0.334
(20)	corr(Δq_t^o, Δq_{t-1}^o)	0.213	(0.211)	0.326

of one-year futures prices implied by our model coincides with the volatility of one-year futures in the data, 0.2.[16]

Figure 5 depicts the impulse response function for a one standard deviation demand shock. The shock follows a hump-shaped pattern with a peak in year seven. On impact, firms cannot change their extraction rates so the price increases one to one with the demand shock. In the following periods, the price of oil increases but the magnitude of this increase is moderated by a rise in the extraction rate. Production rises and reserves are depleted. Since the shock is very persistent, investment rises to increase future reserves and production in order to take advantage of the extended period of high oil prices.

Figure 5: Impulse response to a demand shock

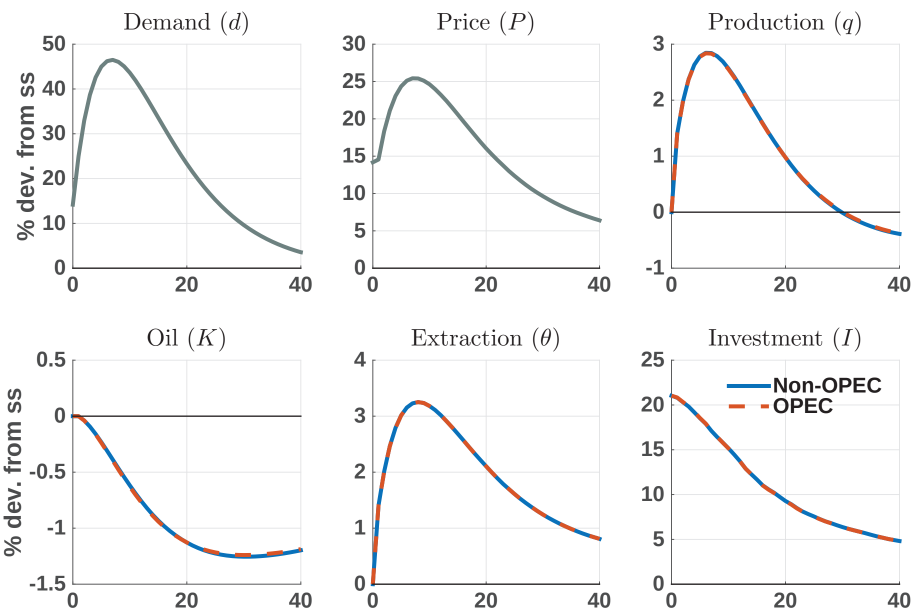
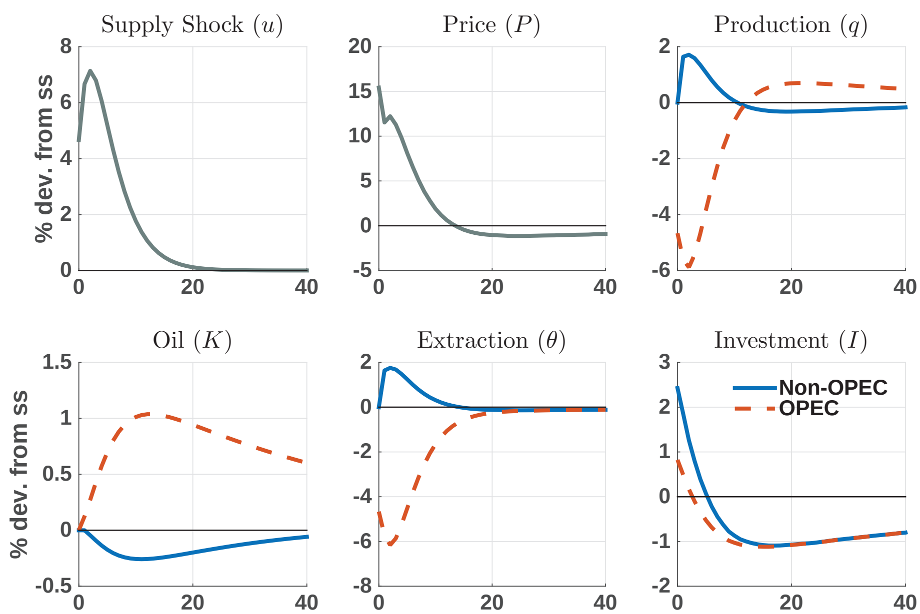


Figure 6 depicts the impulse response function for a one standard deviation supply

[16]Our data for oil futures covers the period from 1986 to 2015. We constructed annual real future oil prices by averaging all the future contracts with one-year maturity within year t and deflating the average by the time t consumer price index. See Alquist et al. (2013) for a discussion of the properties of oil price futures.

shock. The shock follows a hump-shaped pattern with a peak in year 2. Compared to the demand shock, the supply shock is less persistent and is smaller in magnitude. Extraction rates and production rise in non-OPEC firms and fall in OPEC firms. Non-OPEC firms increase their investment to boost reserves so they can raise production. But since the shock is short lived, the rise in investment is much smaller than the one that occurs in response to a demand shock. OPEC firms also raise their investment but not as much as non-OPEC since in the short run OPEC firms have a lower extraction rate than non-OPEC firms.

Figure 6: Impulse response to a supply shock



We can use our model to answer a classic question: what is the role of demand and supply shocks? Table 8 illustrates the role played by demand and supply shocks in the performance of the model. Eliminating demand shocks leads to a small decline in the volatility of prices and to a large decline in the volatility of investment. Eliminating supply shocks leads to a small decline in the volatility of prices, to a large decline in the volatility of OPEC production, and implies a perfect correlation between OPEC

Table 8: Moments sensitivity to demand and supply shocks

Moment	**Data**	(s.e.)	Bench.	No demand shocks	No supply shocks
$std(\Delta p_t)$	0.273	(0.028)	0.227	0.165	0.156
$std(\Delta i_t^n)$	0.192	(0.024)	0.213	0.028	0.211
$std(\Delta i_t^o)$	0.193	(0.027)	0.211	0.011	0.211
$std(\Delta q_t^n)$	0.022	(0.003)	0.025	0.018	0.017
$std(\Delta q_t^o)$	0.069	(0.011)	0.054	0.051	0.017
$corr(\Delta q_t^n, \Delta q_t^o)$	-0.141	(0.125)	0.01	-0.303	1.00

and non-OPEC production levels.

Table 9 provides a variance decomposition for the key variables in our model: price, production and investment. We see that demand and supply shocks contribute roughly equally to the volatility of prices. This result reflects the fact that demand and supply shocks tend to have a similar short-run impact on the price of oil (see Figures 5 and 6). This result is consistent with the importance of macroeconomic performance in driving oil prices emphasized in Barsky and Kilian (2001) and Barsky and Kilian (2004).

Table 9 also shows that the volatility of investment is predominantly driven by demand shocks. These shocks are long-lived and so they elicit a large response of investment (see Figure 5). In contrast, supply shocks have a much lower impact on investment because these shocks are less persistent (see Figure 6).

Table 9: Variance decomposition

Moment	**Shocks**	
	Demand	Supply
$std(\Delta p_t)$	47.2%	52.8%
$std(\Delta i_t^n)$	98.3%	1.7%
$std(\Delta i_t^o)$	99.7%	0.3%
$std(\Delta q_t^n)$	48.3%	51.7%
$std(\Delta q_t^o)$	10.1%	89.9%

Demand and supply shocks contribute equally to the volatility of production by non-OPEC firms. In contrast, the volatility of production by OPEC firms is dominated by supply shocks.

4.2 Modeling OPEC as a cartel

Our model assumes that oil firms are competitive. It would be interesting to study the properties of a version of our model in which OPEC firms behave as a cartel and non-OPEC firms are a competitive fringe. Stiglitz (1976) and Hassler et al. (2010) solve for an equilibrium in which the oil market is controlled by a monopolist that faces a demand with constant elasticity. A version of our model in which OPEC behaves as a cartel is significantly more challenging to solve for three reasons. First, there is a sizable competitive fringe, so the cartel faces a residual demand that is endogenous and does not have constant elasticity. Second, in our model the extraction decision has a dynamic element because the marginal cost function of oil at time t is a function of all past investment decisions. Third, and most importantly, a version of our model in which OPEC is a cartel involves a complex dynamic game. In particular, the cartel can influence its future competition by manipulating today's oil prices in order to influence the investment decisions of its competitors. It is challenging to solve the resulting game even if we assume perfect commitment on the part of the cartel. We leave this task for future research.

Here, we take two modest steps towards investigating the potential impact of non-competitive behavior by OPEC on our results. First, we solved a version of the model in which OPEC firms behave as a cartel for one period and behave competitively thereafter. Non-OPEC act as a competitive fringe in all periods. We find that the response of this economy to demand and supply shocks is similar quantitatively and qualitatively to the impulse response functions we discuss in the previous section.

Second, we re-estimate the model allowing demand and supply shocks to be correlated. One interpretation of this correlation is that it might be induced by non-competitive behavior on the part of OPEC firms; for example, OPEC firms can be thought to change their supply so as to smooth oil prices. We present the results in two tables included in the Appendix. Table 12 reports our parameter estimates and Table 13 the implications of this version of the model for the moments targeted in the estimation. The estimated correlation between innovations to demand and supply (ε^d and ε^u) is -0.64. This negative correlation is consistent with the smoothing hypothesis: OPEC firms cut production when demand is low. The fit of this version of the model is very similar to the fit of the version with independent shocks.

4.3 Robustness

In this section we discuss the results of two robustness exercises. First we consider two alternative instruments for the price of oil. Second, we exclude from the sample two countries for which the data might have larger measurement error (Saudi Arabia and Venezuela). The tables with our robustness results are included in the appendix.

In our benchmark results we instrumented the price of oil with the forecast of the cyclical component of world GDP. Here we consider two alternative instruments for oil prices: copper prices, as in Newell et al. (2016), and the IMF's metals price index. We deflate both indexes by the U.S. consumer price index. Tables 16 and 21 show our estimates of the elasticity of the extraction rate with respect to prices. These estimates are still quite low (0.26 and 0.20 instrumenting with real copper and metals prices, respectively) but are higher than our benchmark estimate (0.12).

Tables 17 and 22 report the elasticity of the extensive margin (number of oil fields in operation) with respect to the real price of oil. As in our benchmark results we find that this elasticity is not significantly different from zero.

Tables 18 and 23 contain our estimates of η obtained using real copper prices and real metals prices as instruments. Both instruments yield a lower value of η. Our estimates of η for non-OPEC are 9.3 in the benchmark case, 4.1 with real copper prices as an instrument, and 4.4 with real metals prices. We re-estimated the model with these values of η and report the results in Tables 19, 20, 24, and 25. The fit of the two alternative models with $\eta = 4.1$ and $\eta = 4.4$ is only slightly worse than the fit of the benchmark model. The parameter estimates are similar across the three models. The main difference is that demand shocks are more persistent in the models with $\eta = 4.1$ or $\eta = 4.4$ than in the benchmark model.

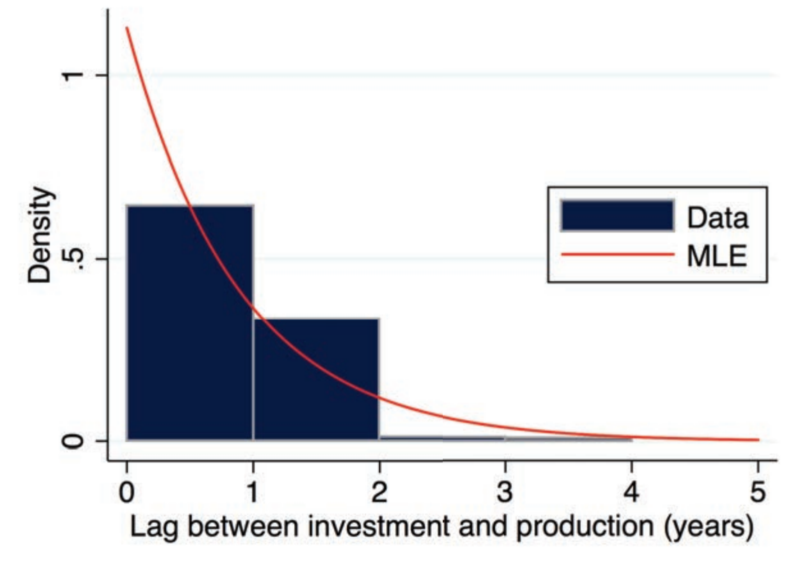
Next we redo our analysis excluding Saudi Arabia and Venezuela from the sample. Our motivation is the possibility of larger measurement error for these two countries. Table 26 shows the estimates of the elasticity of the extraction rate with respect to prices obtained using this restricted sample. This estimate (0.15) is similar to our benchmark estimate (0.12). Table 27 reports the elasticity of the extensive margin (number of oil fields in operation) with respect to the real price of oil. As in our benchmark results we find that this elasticity is not significantly different from zero. We re-estimated our structural model excluding Saudi Arabia and Venezuela from the countries used to compute the data moments. The point estimates of the data moments are very similar to those of the full sample and, as a result, the estimated parameters and model fit are quite similar to those obtained in the benchmark specification (see Tables 29 and 30).

5 The impact of hydraulic fracturing

The advent of hydraulic fracturing (*fracking*) is transforming the oil industry, making the U.S. once again one of the world's top oil producers.[17] We study the quantitative impact of fracking using an extended version of our model that incorporates fracking firms. Since our dataset includes the universe of oil fields in operation, it allows us to compare the properties of conventional oil fields with the properties of oil fields explored using fracking. We find that fracking operations differ greatly from conventional oil production in terms of production flexibility and lags between investment and production. Our model implies that an expansion in the share of fracking production in total oil production will result in a sizable decline in the volatility of oil prices.

[17]See Kilian (2016) and Gilje et al. (2016) for a discussion of the impact of fracking on oil and gasoline markets.

Figure 7: Empirical dist. of lags between investment to production - fracking fields



There are two important differences between fracking and conventional forms of oil production. First, the lag between investment and production is much shorter for fracking operations. Second, it is much less costly to adjust the extraction rate in fracking operations than in conventional oil operations.[18]

Figure 7 shows the distribution of the lag between investment and the first year of production in non-conventional oil fields. Our maximum likelihood estimator of λ is 1.13, so the average lag between investment and production is about one year. Recall that this lag is 12 years for conventional production.

Table 11 reports our estimates of η for fields explored with fracking obtained using the cyclical component of world real GDP as an instrument. We see that for non-conventional oil fields our estimate of η is roughly 1.7. In contrast, when we include all

[18]One piece of evidence that suggests that fracking operations are highly flexible is the data compiled by Baker Hughes on the number of oil rigs in operation in the U.S. In January 2009, there were 345 rigs in operation. By September 2014, this number had risen to 1,600. Most of the new rigs are likely to be used in fracking. Between September 2014 and February 2016 oil prices plummeted from 93 to 30 dollars per barrel. Between September 2014 and September 2015, the number of oil rigs declined from 1,600 to 641. By the end of February 2016, the number of rigs in operation was reduced to 400.

Table 10: Extraction rate adjustment costs regression - fracking fields

Variable	**(1)**	**(2)**
ln(extraction)	1.68***	9.30***
	(0.34)	(1.14)
Oil field FE	✓	✓
Year of operation FE	✓	✓
Sample	Fracking fields	All non-OPEC
IV	✓	✓
1^{st} stage F-stat	9.1	53
Clusters (oil fields)	952	9,969
Observations	4,940	146,879

oil fields in our sample in the regression, we obtain an estimate of $\eta = 9.3$.

To study the impact of fracking, we include in our model a third type of firm that produces oil using fracking. These firms have extraction costs that are less convex ($\eta^F = 1.7 < 9.3$), no lag between investment and production ($\lambda^F = 1$), and no lag in the adjustment of the extraction rate. We also assume that fracking firms are not subject to supply shocks.

There is a continuum of measure one of fracking firms. The problem of the representative firm is to maximize its value (V^F):

$$\max_{\left\{I_t^F, \theta_{t+1}^F, K_{t+1}^F, X_{t+1}^F\right\}} V^F = E_0 \sum_{t=0}^{\infty} \beta^t \left[P_t \theta_t^F K_t^F - I_t^F - \psi^F \left(\theta_t^F\right)^{\eta^F} K_t^F \right], \tag{12}$$

subject to

$$X_{t+1}^F = (1 - \lambda^F) X_t^F + \left(I_t^F\right)^{\alpha} \left(L^F\right)^{1-\alpha} \tag{13}$$

$$K_{t+1}^F = (1 - \theta_t^F) K_t^F + \lambda^F X_{t+1}^F. \tag{14}$$

Here, I_t^F denotes investment, θ_t^F the extraction rate, X_t^F oil in process, K_t^F oil reserves, and L^F the land available to the fracking firm.

We assume that the convexity of extraction costs is lower for fracking firms: $\eta^F < \eta$. This assumption does not imply that the average and marginal cost of extraction for fracking firms are different than those of the traditional firms, as this comparison also depends on ψ^F and on the equilibrium levels of reserves and extraction rates. The optimality conditions for fracking firms are identical to those for non-OPEC firms.

Total production is now given by:

$$\boldsymbol{\theta}_t^N \mathbf{K}_t^N + e^{-u_t} \boldsymbol{\theta}_t^O \mathbf{K}_t^O + \boldsymbol{\theta}_t^F \mathbf{K}_t^F = q_t,$$

where $\mathbf{K}_t^F$ and $\boldsymbol{\theta}_t^F$ denote the aggregate reserves and aggregate extraction rate of fracking firms, respectively.

These new forms of oil production are only feasible in some parts of the globe. Rystad estimates that they will represent 20 percent of oil production by 2050. We calibrate ψ^F and the amount of land available for fracking to satisfy two properties. First, in the steady state fracking represents 20 percent of total oil production. Second, the steady-state extraction rate for fracking coincides with the one in our data (1.2 percent).

In equilibrium, the marginal return to investing in fracking is equal to that of investing in conventional oil production. Our calibration implies that the steady state marginal cost of extracting a barrel of oil is 19 percent higher for fracking firms than for conventional production. This higher production cost is compensated by the shorter lag between investment and production associated with fracking.

Figures 8 and 9 show the impulse response for a demand and supply shock, respectively. The panels for the price response also include the price response in our benchmark model without fracking firms. We see that fracking firms respond much more to the shock, in terms of production, extraction and investment, than non-fracking firms. The result is a much lower increase in the price of oil.

Comparing the response of conventional firms in a world with (Figures 8 and 9) and without fracking (Figures 5 and 6), we see that conventional firms respond much less to shocks in a world with fracking firms. Since fracking firms are more nimble, they respond rapidly to shocks, moderating the equilibrium price increase and making it less

Figure 8: Impulse response to a demand shock - fracking

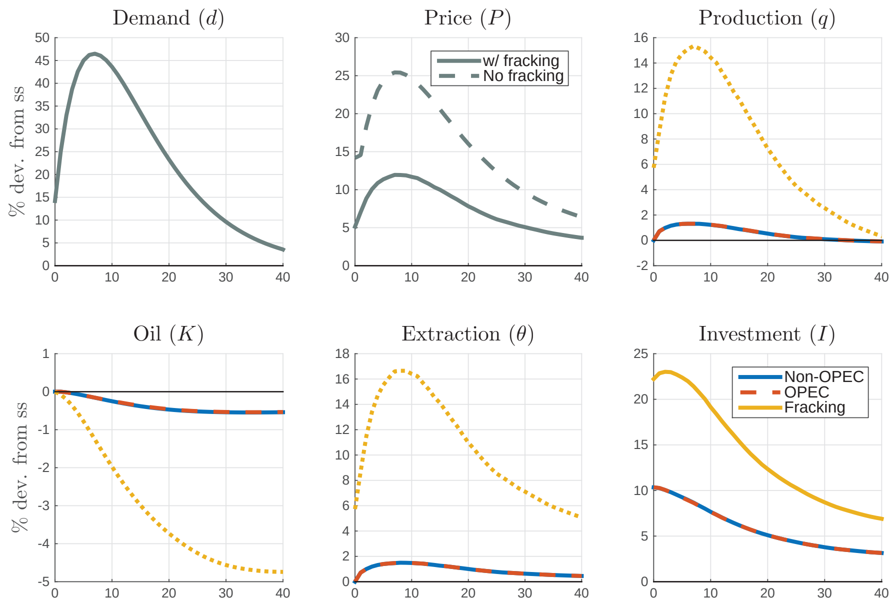


Figure 9: Impulse response to a supply shock - fracking

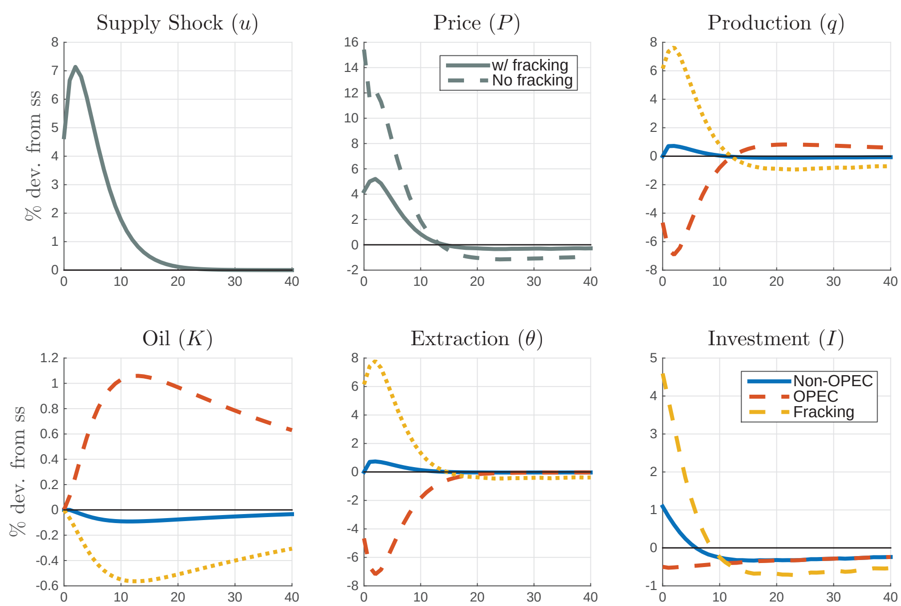


Table 11: Implication of fracking on key aggregate moments

	Moment	Benchm. model	Model w/ fracking
(1)	$std(\Delta p_t)$	0.23	0.08
(2)	$std(\Delta i_t)$	0.21	0.12
(3)	$std(\Delta q_t)$	0.03	0.02
(4)	$corr(\Delta p_t,\, \Delta i_t)$	0.69	0.7
(5)	$corr(\Delta p_t,\, \Delta q_t)$	-0.47	0.6
(6)	$corr(\Delta q_t,\, \Delta i_t)$	-0.06	0.53

profitable for conventional firms to change their investment and extraction rates.

Table 11 compares the implications of versions of the model with and without fracking for some key moments. We find that the main impact of fracking is to reduce the volatility of oil prices by 65 percent from 0.23 to 0.08. Investment and production are also less volatile in the version of the model with fracking. In addition, there is also a higher correlation between prices and quantities, and between investment and quantities, reflecting the response of fracking firms to high-frequency movements in prices.

6 Conclusion

Our paper reviews some key facts about the oil market and proposes a simple industry equilibrium model that is consistent with these facts.

We leave four interesting projects for future research. The first is to develop a richer model of firm heterogeneity. In our model there are only two types of firms, OPEC and non-OPEC. In practice, firms in both groups differ in their attributes which results in different choices of investment and extraction rates. The second is to study a version of our model in which OPEC firms act as a cartel while non-OPEC firms are a competitive fringe. The third is to introduce the possibility of above-ground inventories that can be used by commodity speculators to respond to high-frequency changes in oil prices.[19]

[19] See Deaton and Laroque (1992), Deaton and Laroque (1996), Kilian and Murphy (2014), and

The fourth is to combine our model of the oil market with a fully-fledged model of the world economy. Such a combined model would allow us to study the effect of energy-saving technical change and evaluate the impact of solar, wind, and other alternative energy sources on the dynamics of the oil markets and the world economy.

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Appendix

A Additional tables

Table 12: Estimated parameters when shocks are correlated

Parameter	**Benchm. model**	(s.e.)	**Model w/ corr. shocks**	(s.e.)
ϵ	0.135	(0.015)	0.084	(0.013)
α	3×10^{-6}	(0.978)	1×10^{-7}	(0.674)
ρ_1^d	1.761	(0.075)	1.759	(0.089)
ρ_2^d	-0.775	(0.073)	-0.773	(0.09)
ρ_1^u	1.428	(0.15)	1.719	(0.072)
ρ_2^u	-0.51	(0.11)	-0.733	(0.063)
$var(e_t^d)$	0.02	(0.007)	0.05	(0.018)
$var(e_t^u)$	0.002	(0.001)	0.002	(0.001)
$corr(e_t^d, e_t^u)$	-	-	-0.639	(0.105)

Table 13: Data and model moments when shocks are correlated

	Moment	**Data**	(s.e.)	**Benchm. model**	**Model w/ corr. shocks**
(1)	std(Δp_t)	0.273	(0.028)	0.227	0.232
(2)	std(Δi_t^n)	0.192	(0.24)	0.213	0.205
(3)	std(Δi_t^o)	0.193	(0.27)	0.211	0.216
(4)	std(Δq_t^n)	0.022	(0.003)	0.025	0.022
(5)	std(Δq_t^o)	0.069	(0.011)	0.054	0.072
(6)	corr(Δp_t, Δi_t^n)	0.557	(0.147)	0.709	0.749
(7)	corr(Δp_t, Δi_t^o)	0.362	(0.109)	0.657	0.53
(8)	corr(Δp_t, Δq_t^n)	0.031	(0.069)	0.049	0.003
(9)	corr(Δp_t, Δq_t^o)	0.030	(0.122)	-0.572	-0.418
(10)	corr(Δi_t^n, Δi_t^o)	0.673	(0.096)	0.997	0.946
(11)	corr(Δi_t^n, Δq_t^n)	0.087	(0.094)	-0.001	0.008
(12)	corr(Δi_t^n, Δq_t^o)	0.023	(0.112)	-0.103	0.027
(13)	corr(Δi_t^o, Δq_t^n)	-0.034	(0.145)	0.003	0
(14)	corr(Δi_t^o, Δq_t^o)	-0.226	(0.153)	-0.036	0.251
(15)	corr(Δq_t^n, Δq_t^o)	-0.141	(0.125)	0.014	-0.221
(16)	corr(Δp_t, Δp_{t-1})	-0.027	(0.088)	-0.018	-0.125
(17)	corr(Δi_t^n, Δi_{t-1}^n)	0.119	(0.135)	0.008	0.025
(18)	corr(Δi_t^o, Δi_{t-1}^o)	0.311	(0.096)	0.009	0.022
(19)	corr(Δq_t^n, Δq_{t-1}^n)	0.643	(0.113)	0.334	0.46
(20)	corr(Δq_t^o, Δq_{t-1}^o)	0.213	(0.211)	0.326	0.671

B Robustness Tables

B.1 Sample period starting at 1900

Table 14: Price elasticity of extraction rates (1900–2015)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ln(price)	0.06*** (0.006)	0.09*** (0.008)	0.12*** (0.009)	0.14*** (0.01)	0.16*** (0.011)
ln(price) $\times \mathbb{1}_{\text{OPEC}}$			−0.21*** (0.022)	−0.2*** (0.023)	
ln(price) $\times \mathbb{1}_{\text{Big Firm}}$				−0.06*** (0.018)	
ln(price) $\times \mathbb{1}_{\lvert\Delta \ln(p)\rvert>0.1}$					−0.15*** (0.01)
Oil field FE	✓	✓	✓	✓	✓
Operation year FE	✓	✓	✓	✓	✓
Year trend	✓	✓	✓	✓	✓
IV	✗	✓	✓	✓	✓
Clusters (oil fields)	13,811	13,372			
Observations	351,442	351,003			

Oil fields with positive extraction in 1901-2015, excluding last year of operation. Standard errors in parenthesis. Instrument for price using one year lagged price (F-stat > 1000 in (2)-(5)). $(***)$ - significant at a 1% level.

Table 15: Price elasticity of oil fields in operation (1900–2015)

Variable	**(1)**	**(2)**	**(3)**	**(4)**
ln(price)	-0.4	-0.51	-0.18	-0.32
	(0.27)	(0.32)	(0.13)	(0.19)
Year trend	✓	✓	✓	✓
IV	✗	✓	✓	✓
Dep. variable	All fields	All fields	Non-OPEC fields	OPEC fields
Observations	114	114	114	114

Newey-West standard errors with 5 years lag in parenthesis.

B.2 Instrument with real copper prices

Table 16: Price elasticity of extraction rates

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ln(price)	0.09***	0.26***	0.31***	0.34***	0.22***
	(0.009)	(0.018)	(0.019)	(0.021)	(0.018)
ln(price) $\times \mathbb{1}_{\text{OPEC}}$			−0.25***	−0.24***	
			(0.041)	(0.041)	
ln(price) $\times \mathbb{1}_{\text{Big Firm}}$				−0.1***	
				(0.032)	
ln(price) $\times \mathbb{1}_{\lvert\Delta \ln(p)\rvert>0.1}$					−0.03***
					(0.005)
Oil field FE	✓	✓	✓	✓	✓
Operation year FE	✓	✓	✓	✓	✓
Year trend	✓	✓	✓	✓	✓
IV	✗	✓	✓	✓	✓
Clusters (oil fields)	12,187		11,479		
Observations	173,742		173,034		

Oil fields with positive extraction in 1971-2015, excluding last year of operation. Standard errors in parenthesis. Instrument for price using real copper price prediction (F-stat > 1000 in (2)-(5)). $(***)$ - significant at a 1% level.

Table 17: Price elasticity of oil fields in operation

Variable	**(1)**	**(2)**	**(3)**	**(4)**
ln(price)	−0.05	−0.44	−0.13	−0.31
	(0.06)	(0.29)	(0.10)	(0.19)
Year trend	✓	✓	✓	✓
IV	✗	✓	✓	✓
Dep. variable	All fields	All fields	Non-OPEC fields	OPEC fields
Observations	45	45	45	45

Newey-West standard errors with 5 years lag in parenthesis.

Table 18: Extraction rate adjustment costs regression

Variable	**(1)**	**(2)**	**(3)**
ln(extraction)	4.54***	4.05***	15.19**
	(0.22)	(0.18)	(7.72)
Oil field FE	✓	✓	✓
Operation year FE	✓	✓	✓
Sample	All	Non-OPEC	OPEC
IV	✓	✓	✓
1^{st} stage F-stat	276	198	3.4
Clusters (oil fields)	11,527	9,969	1,558
Observations	174,339	146,879	27,460

Table 19: Estimated parameters

Parameter	Estimate	(s.e.)
ϵ	0.077	(0.014)
α	0.062	(0.079)
ρ_1^d	1.991	(0.003)
ρ_2^d	-0.991	(0.003)
ρ_1^u	1.729	(0.077)
ρ_2^u	-0.748	(0.072)
$var(e_t^d)$	0.001	(0.000...)
$var(e_t^u)$	0.001	(0.000...)

Table 20: Data and model moments

	Moment	Data	(s.e.)	Benchm. model	Model w/ copper IV
(1)	std(Δp_t)	0.273	(0.028)	0.227	0.195
(2)	std(Δi_t^n)	0.192	(0.24)	0.213	0.228
(3)	std(Δi_t^o)	0.193	(0.27)	0.211	0.217
(4)	std(Δq_t^n)	0.022	(0.003)	0.025	0.025
(5)	std(Δq_t^o)	0.069	(0.011)	0.054	0.034
(6)	corr(Δp_t, Δi_t^n)	0.557	(0.147)	0.709	0.621
(7)	corr(Δp_t, Δi_t^o)	0.362	(0.109)	0.657	0.484
(8)	corr(Δp_t, Δq_t^n)	0.031	(0.069)	0.049	-0.051
(9)	corr(Δp_t, Δq_t^o)	0.030	(0.122)	-0.572	-0.357
(10)	corr(Δi_t^n, Δi_t^o)	0.673	(0.096)	0.997	0.977
(11)	corr(Δi_t^n, Δq_t^n)	0.087	(0.094)	-0.001	0.228
(12)	corr(Δi_t^n, Δq_t^o)	0.023	(0.112)	-0.103	-0.066
(13)	corr(Δi_t^o, Δq_t^n)	-0.034	(0.145)	0.003	0.238
(14)	corr(Δi_t^o, Δq_t^o)	-0.226	(0.153)	-0.036	0.095
(15)	corr(Δq_t^n, Δq_t^o)	-0.141	(0.125)	0.014	-0.198
(16)	corr(Δp_t, Δp_{t-1})	-0.027	(0.088)	-0.018	-0.108
(17)	corr(Δi_t^n, Δi_{t-1}^n)	0.119	(0.135)	0.008	0.295
(18)	corr(Δi_t^o, Δi_{t-1}^o)	0.311	(0.096)	0.009	0.324
(19)	corr(Δq_t^n, Δq_{t-1}^n)	0.643	(0.113)	0.334	0.591
(20)	corr(Δq_t^o, Δq_{t-1}^o)	0.213	(0.211)	0.326	0.609

B.3 Instrument with real metal prices

Table 21: Price elasticity of extraction rates

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ln(price)	0.09***	0.20***	0.24***	0.26***	0.07***
	(0.009)	(0.016)	(0.018)	(0.02)	(0.014)
ln(price) $\times \mathbb{1}_{\text{OPEC}}$			−0.22***	−0.21***	
			(0.04)	(0.041)	
ln(price) $\times \mathbb{1}_{\text{Big Firm}}$				−0.06*	
				(0.032)	
ln(price) $\times \mathbb{1}_{\lvert\Delta \ln(p)\rvert>0.1}$					−0.12***
					(0.006)
Oil field FE	✓	✓	✓	✓	✓
Operation year FE	✓	✓	✓	✓	✓
Year trend	✓	✓	✓	✓	✓
IV	✗	✓	✓	✓	✓
Clusters (oil fields)	12,187	11,479			
Observations	173,742	173,034			

Oil fields with positive extraction in 1971-2015, excluding last year of operation. Standard errors in parenthesis. Instrument for price using real metal price index prediction (F-stat > 1000 in (2)-(5)). $***$ [$*$] - significant at a 1% [10%] level.

Table 22: Price elasticity of oil fields in operation

Variable	(1)	(2)	(3)	(4)
ln(price)	-0.05	-0.08	-0.02	-0.06
	(0.06)	(0.07)	(0.02)	(0.06)
Year trend	✓	✓	✓	✓
IV	✗	✓	✓	✓
Dep. variable	All fields	All fields	Non-OPEC fields	OPEC fields
Observations	45	45	45	45

Newey-West standard errors with 5 years lag in parenthesis.

Table 23: Extraction rate adjustment costs regression

Variable	(1)	(2)	(3)
ln(extraction)	4.72***	4.26***	11.73**
	(0.22)	(0.18)	(4.15)
Oil field FE	✓	✓	✓
Operation year FE	✓	✓	✓
Sample	All	Non-OPEC	OPEC
IV	✓	✓	✓
1^{st} stage F-stat	271	286	3.5
Clusters (oil fields)	11,527	9,969	1,558
Observations	174,339	146,879	27,460

Table 24: Estimated parameters

Parameter	Estimate	(s.e.)
ϵ	0.077	(0.013)
α	0.067	(0.087)
ρ_1^d	1.991	(0.003)
ρ_2^d	-0.991	(0.003)
ρ_1^u	1.728	(0.076)
ρ_2^u	-0.746	(0.071)
$var(e_t^d)$	0.001	(0.000...)
$var(e_t^u)$	0.001	(0.000...)

Table 25: Data and model moments

	Moment	Data	(s.e.)	Benchm. model	Model w/ metal IV
(1)	std(Δp_t)	0.273	(0.028)	0.227	0.199
(2)	std(Δi_t^n)	0.192	(0.24)	0.213	0.229
(3)	std(Δi_t^o)	0.193	(0.27)	0.211	0.217
(4)	std(Δq_t^n)	0.022	(0.003)	0.025	0.025
(5)	std(Δq_t^o)	0.069	(0.011)	0.054	0.035
(6)	corr(Δp_t, Δi_t^n)	0.557	(0.147)	0.709	0.621
(7)	corr(Δp_t, Δi_t^o)	0.362	(0.109)	0.657	0.484
(8)	corr(Δp_t, Δq_t^n)	0.031	(0.069)	0.049	-0.041
(9)	corr(Δp_t, Δq_t^o)	0.030	(0.122)	-0.572	-0.372
(10)	corr(Δi_t^n, Δi_t^o)	0.673	(0.096)	0.997	0.977
(11)	corr(Δi_t^n, Δq_t^n)	0.087	(0.094)	-0.001	0.244
(12)	corr(Δi_t^n, Δq_t^o)	0.023	(0.112)	-0.103	-0.076
(13)	corr(Δi_t^o, Δq_t^n)	-0.034	(0.145)	0.003	0.238
(14)	corr(Δi_t^o, Δq_t^o)	-0.226	(0.153)	-0.036	0.087
(15)	corr(Δq_t^n, Δq_t^o)	-0.141	(0.125)	0.014	-0.202
(16)	corr(Δp_t, Δp_{t-1})	-0.027	(0.088)	-0.018	-0.111
(17)	corr(Δi_t^n, Δi_{t-1}^n)	0.119	(0.135)	0.008	0.293
(18)	corr(Δi_t^o, Δi_{t-1}^o)	0.311	(0.096)	0.009	0.323
(19)	corr(Δq_t^n, Δq_{t-1}^n)	0.643	(0.113)	0.334	0.587
(20)	corr(Δq_t^o, Δq_{t-1}^o)	0.213	(0.211)	0.326	0.599

B.4 Excluding Saudi Arabia and Venezuela from the sample

Table 26: Price elasticity of extraction rates

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ln(price)	0.11^{***} (0.009)	0.15^{***} (0.012)	0.17^{***} (0.015)	0.18^{***} (0.02)	0.18^{***} (0.013)
ln(price) $\times \mathbb{1}_{\text{OPEC}}$			-0.17^{***} (0.07)	-0.17^{***} (0.041)	
ln(price) $\times \mathbb{1}_{\text{Big Firm}}$				-0.05 (0.05)	
ln(price) $\times \mathbb{1}_{\lvert\Delta \ln(p)\rvert>0.1}$					-0.18^{***} (0.001)
Oil field FE	✓	✓	✓	✓	✓
Operation year FE	✓	✓	✓	✓	✓
Year trend	✓	✓	✓	✓	✓
IV	✗	✓	✓	✓	✓
Clusters (oil fields)	11,893		11,195		
Observations	167,848		167,150		

Oil fields with positive extraction in 1971-2015, excluding last year of operation. Standard errors in parenthesis. Instrument for price using real metal price index prediction (F-stat > 1000 in (2)-(5)). $***$ [$*$] - significant at a 1% [10%] level.

Table 27: Price elasticity of oil fields in operation

Variable	(1)	(2)	(3)	(4)
ln(price)	−0.03	0.01	−0.01	0.02
	(0.08)	(0.1)	(0.03)	(0.09)
Year trend	✓	✓	✓	✓
IV	✗	✓	✓	✓
Dep. variable	All fields	All fields	Non-OPEC fields	OPEC fields
Observations	45	45	45	45

Newey-West standard errors with 5 years lag in parenthesis.

Table 28: Extraction rate adjustment costs regression

Variable	(1)	(2)	(3)
ln(extraction)	9.97***	9.3***	19.77
	(1.20)	(0.18)	(12.03)
Oil field FE	✓	✓	✓
Operation year FE	✓	✓	✓
Sample	All	Non-OPEC	OPEC
IV	✓	✓	✓
1^{st} stage F-stat	56	53	2.5
Clusters (oil fields)	11,243	9,969	1,274
Observations	168,388	146,879	21,509

Table 29: Estimated parameters

Parameter	**Estimate**	(s.e.)
ϵ	0.122	(0.017)
α	7×10^{-7}	(0.930)
ρ_1^d	1.765	(0.077)
ρ_2^d	-0.779	(0.075)
ρ_1^u	1.529	(0.094)
ρ_2^u	-0.585	(0.092)
$var(e_t^d)$	0.002	(0.001)
$var(e_t^u)$	0.022	(0.008)

Table 30: Data and model moments

		Benchmark			No Saudi Arabia and Venezuela		
	Moment	**Data**	(s.e.)	**Model**	**Data**	(s.e.)	**Model**
(1)	std(Δp_t)	0.273	(0.028)	0.227	0.273	(0.028)	0.226
(2)	std(Δi_t^n)	0.192	(0.024)	0.213	0.192	(0.024)	0.221
(3)	std(Δi_t^o)	0.193	(0.027)	0.211	0.208	(0.031)	0.218
(4)	std(Δq_t^n)	0.022	(0.003)	0.025	0.273	(0.028)	0.024
(5)	std(Δq_t^o)	0.069	(0.011)	0.054	0.076	(0.016	0.049
(6)	corr(Δp_t, Δi_t^n)	0.557	(0.147)	0.709	0.557	(0.147)	0.767
(7)	corr(Δp_t, Δi_t^o)	0.362	(0.109)	0.657	0.36	(0.12)	0.708
(8)	corr(Δp_t, Δq_t^n)	0.031	(0.069)	0.049	0.031	(0.069)	0.061
(9)	corr(Δp_t, Δq_t^o)	0.030	(0.122)	-0.572	-0.025	(0.104)	-0.53
(10)	corr(Δi_t^n, Δi_t^o)	0.673	(0.096)	0.997	0.626	(0.108)	0.995
(11)	corr(Δi_t^n, Δq_t^n)	0.087	(0.094)	-0.001	0.087	(0.094)	0.001
(12)	corr(Δi_t^n, Δq_t^o)	0.023	(0.112)	-0.103	-0.065	(0.112)	-0.145
(13)	corr(Δi_t^o, Δq_t^n)	-0.034	(0.145)	0.003	-0.067	(0.138)	0.004
(14)	corr(Δi_t^o, Δq_t^o)	-0.226	(0.153)	-0.036	-0.357	(0.246)	-0.062
(15)	corr(Δq_t^n, Δq_t^o)	-0.141	(0.125)	0.014	-0.126	(0.089)	0.002
(16)	corr(Δp_t, Δp_{t-1})	-0.027	(0.088)	-0.018	-0.027	(0.088)	-0.019
(17)	corr(Δi_t^n, Δi_{t-1}^n)	0.119	(0.135)	0.008	0.119	(0.135)	0.009
(18)	corr(Δi_t^o, Δi_{t-1}^o)	0.311	(0.096)	0.009	0.252	(0.11)	0.01
(19)	corr(Δq_t^n, Δq_{t-1}^n)	0.643	(0.113)	0.334	0.643	(0.113)	0.381
(20)	corr(Δq_t^o, Δq_{t-1}^o)	0.213	(0.211)	0.326	0.349	(0.154)	0.401