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Abstract:
Knowledge about rig markets is crucial for understanding the global oil market. In this paper we first develop a simple bargaining model for rig markets. Then we examine empirically the most important drivers for rig rate formation of floaters operating at the Norwegian Continental Shelf in the period 1991q4 to 2013q4. We use reduced form time series models with two equations and report conditional point and bootstrapped interval forecasts for rig rates and capacity utilization. We then consider two alternative simulations to examine how the oil price and remaining petroleum reserves influence rig rate formation of floaters. In the first alternative simulation we assume a relatively high crude oil price equal to 100 USD (2010) per barrel for the entire forecast period, whereas the reference case features the actual oil price with extrapolated values for the last quarters in the forecast period. According to our results, the rig rates will be about 34 percent higher in 2016q4 with the higher oil price. In the second alternative simulation we explore the effects of opening the Barents Sea and areas around Jan Mayen for petroleum activity. This contributes to dampening the fall in the rig rates and capacity utilization over the last part of the forecast period.

Keywords: Rig rates; Capacity utilization; Oil price; Forecasting; Bootstrapping

JEL classification: C32; C51; C53; L71; Q47

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Sammendrag

Vi analyserer utviklingen i gjennomsnittlige riggrater og kapasitetsutnytting knyttet til virksomheten på norsk kontinentalsokkel. Vi benytter en to-ligningsmodell spesifisert for kvartalsvise data. Tidsperioden som betraktes strekker seg fra fjerde kvartal 1991 til utgangen av 2013. I tillegg rapporterer vi simulerte prediksjoner for den gjennomsnittlige riggraten og kapasitetsutnyttingen for de 12 påfølgende kvartalene. Ved siden av referansesimuleringen, rapporterer vi også prediksjoner for to alternative simuleringer. I det første alternativet antar vi en vedvarende høy oljepris svarende til 100 amerikanske dollar i konstante 2010-priser for hele prediksjonsperioden, mens vi i referansesimuleringen bruker den observerte oljeprisen forlenget med noen fremskrevne verdier. Ifølge våre resultater ville den gjennomsnittlige riggraten ligge om lag en tredel høyere i fjerde kvartal 2016 ved en vedvarende høy oljepris, sammenlignet med referansesimuleringen. I den andre alternative simuleringen undersøker vi effekten av å åpne Barentshavet og området rundt Jan Mayen for petroleumsaktivitet. Økningen i petroleumsreservene som følge av dette bidrar til å dempe fallet i den gjennomsnittlige riggraten og kapasitetsutnyttingen som forekommer i referansesimuleringen.

1. Introduction

More than one third of global hydrocarbon supply is extracted offshore and the share is increasing. A major determinant of offshore hydrocarbon production is the cost of exploration and well development, where rigs play a key role. Therefore, examining rig markets is crucial for understanding the global oil market. Moreover, the rig industry itself is a multibillion industry of considerable interest. In this paper we examine rig rate formation and utilization rates for floaters on the Norwegian Continental Shelf (NCS). Floaters are rigs that can operate on deep water, and consist of semisubmersibles and drillships, as opposed to jack-ups that can only operate on more shallow water.

Petroleum activity on the NCS started with the discovery of the Ekofisk field in 1969, one of the world's largest offshore oil fields discovered so far. Following Ekofisk was a surge in optimism regarding the resource potential on the NCS, and during the next two decades major offshore oil and gas fields were discovered and developed in quick succession.[1] In 2014, Norwegian oil and gas production accounted for, respectively, 2.0 percent and 3.1 percent of global oil and gas production (BP, 2015), and in 2012 Norway was the 3rd largest exporter of natural gas in the world and the 10th largest net exporter of oil (Norwegian Petroleum Directorate, 2014).

Petroleum production on the NCS is still dominated by production from the large fields discovered in the 1970s. As these fields mature, petroleum extraction declines, and total oil production on the NCS peaked in 2001. The Norwegian government has tried to counteract this development by policies tailored to spur exploration and development.[2] Figure 1 indicates that these policies, along with high oil prices, have induced more explorative activity on the NCS. The figure also emphasizes two other interesting points. First, drilling costs constitute a major part of exploration costs. Second, petroleum exploration has become more costly, partly because the cost of drilling has increased substantially in recent years. Higher drilling costs are important because drilling affects both the profitability of existing fields and the cost of exploration.[3] While drilling is the major purpose of rig activity, rigs also provide services such as workovers and plugging during the entire lifetime of an oil and gas field.

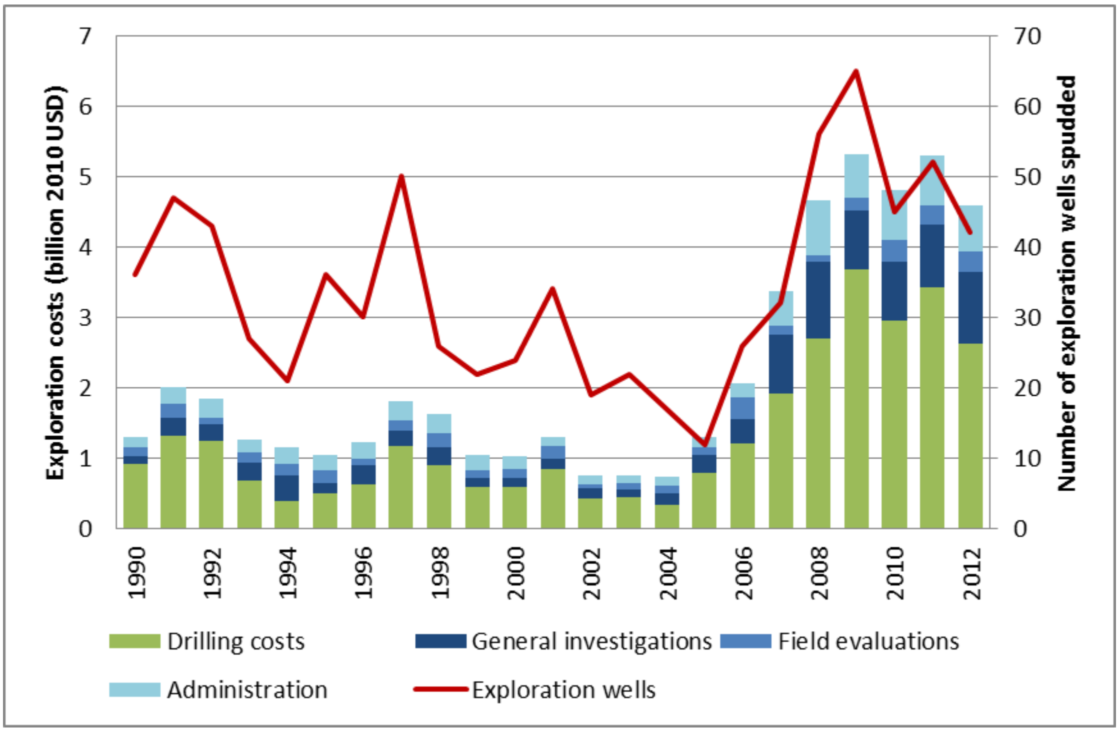
[1] The fields include, e.g., Statfjord, Troll, Oseberg and Gullfaks, all discovered in the 1970's.

[2] This includes allowance of petroleum activity expansion into new areas such as the southern parts of the Barents Sea. Further, since 2005, companies that are not in a positive tax position can claim reimbursement of the tax value of exploration costs. Recent years have seen major discoveries such as Johan Sverdrup in the North Sea and Johan Castberg in the Barents Sea.

[3] The Ministry of Petroleum and Energy (2012, p. 19) estimates that a 30 percent reduction in drilling cost of production and exploration wells from floating platforms will increase the net present value of petroleum resources on the NCS by more than 1000 billion NOK(2012) (172 billion 2012 USD). The estimate is based on an oil price of 90 USD per barrel.

Approximately 80 percent of the rig capacity on the NCS in 2011 was used for drilling of new exploration and production wells (Ministry of Petroleum and Energy, 2012).

Figure 1. Exploration costs (left axis) and number of spudded exploration wells (right axis) on the NCS. Source: Norwegian Petroleum Directorate (http://www.npd.no/en)



Increased offshore exploration costs are not particular for the NCS, see e.g. EIA (2011, p. 111). Indeed, the cost of drilling has increased worldwide and, as pointed out by Osmundsen *et al.* (2015), this cost increase has likely been one of the main factors behind the increase in oil and gas prices over the last decade. According to Osmundsen *et al.* (2010a), higher drilling costs observed on the NCS in the period 2004-2008 were partly due to increased rig rates and partly due to reduced drilling speed. Moreover, drilling speed tends to be negatively correlated with capacity utilization, due to bottlenecks and lower drilling quality (Osmundsen *et al.*, 2010b). These features highlight the importance of understanding rig markets, including rig rates and capacity utilization.

The contribution of the present paper is twofold: The first part is to improve our understanding of rig markets in general and on the NCS in particular. We present a simple theoretical model to sharpen our understanding of rig markets and identify the most important drivers for rig rate formation. Then we estimate their effects based on data for the NCS, and finally we present forecasts for rig rates and capacity utilization on the NCS. Our second contribution is related to the fact that the rig market data offer some challenges related to data aggregation and construction of quarterly time series that are of interest from an econometric perspective. For example, we may have several observations (contracts about future work) of one rig within one quarter.

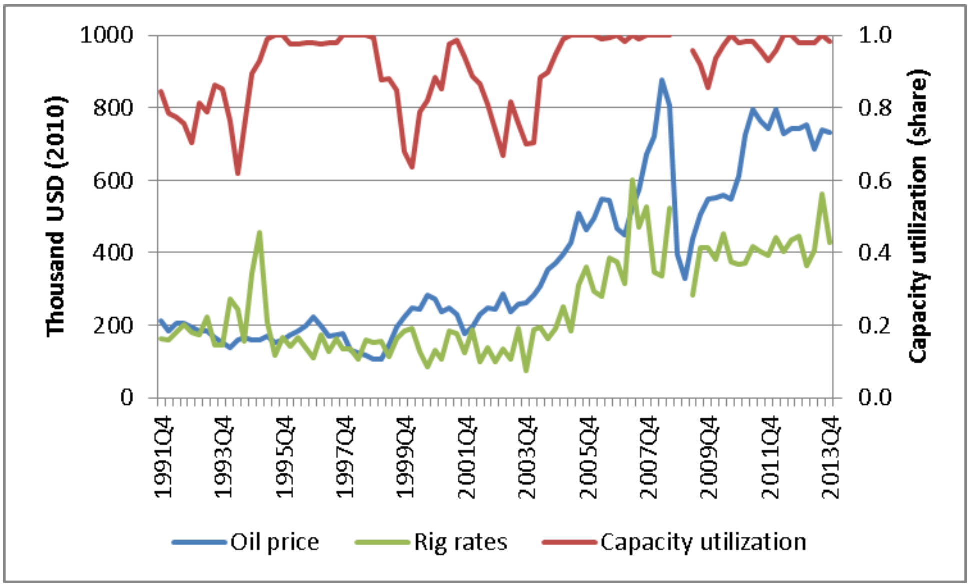
Our theoretical model solves for the rig rate and hired rig days simultaneously, given demand and supply for rigs as determined by exogenous variables like the oil price and petroleum resource potential. The model highlights that an empirical model of the rig market should model both supply and demand for rigs in order to separate demand and supply side effects. For example, a lower oil price yields lower expected profitability and, hence, rig demand declines. Keeping rigs idle is very costly for the rig companies, however, causing aggressive bidding.[4] Thus, rig rates will decline, and exploration, development and new production well drilling become cheaper. This supply side effect dampens the decline in activity from lower oil price, via lower rig rates.

We then build and estimate a reduced form two-equation econometric model for rig rates and a proxy for capacity utilization in the NCS rig market for floaters over the period 1990q4 to 2013q4, based on detailed data on rig contracts and rig characteristics from the shipbroking company Clarksons Platou Offshore. The two equation framework allows us to account for both supply and demand effects in the rig market. The two endogenous variables are shown in Figure 2, together with the Brent Blend oil price. Note that the rig rate series is calculated based on data on individual rig contracts (see Section 3 for details), whereas the capacity utilization series is taken directly from the Clarksons Platou Offshore data. The figure shows that rig rates are volatile and, not surprisingly, suggests a positive correlation between rig rates and the oil price. We also examine the effects of various rig characteristics, rig contract features, and other potentially relevant variables such as estimates of remaining reserves/resources and regulatory changes.

In our estimations we construct quarterly time series from rig market data and specify a non-linear reduced form model for mean log rig rates and capacity utilization. The latter variable is bounded on the [0,1] interval, and we take account of this feature by utilizing the logit transformation for specifying the capacity utilization equation. In most of the models, consistent estimation may be obtained by estimating the rig rate equation by single equation non-linear least squares and the capacity utilization equation by ordinary least squares, but our specification implies that there will be efficiency gains in joint estimation of the two-equations. Hence, all our models will be estimated by non-linear multivariate regression, cf. for instance Seber and Wild (1989, Ch. 11).

[4] Rigs can be ready stacked, i.e. kept idle but operational, or cold stacked (Corts, 2008). Cold stacking involves reducing the crew to either zero or just a few key individuals and storing the rig in a harbor, shipyard or designated area offshore. See more at: http://www.rigzone.com/data/rig_statusdescriptions.asp

Figure 2. Oil price (per ktoe, Brent blend) (left axis), rig rates (mean day rates for floaters on the NCS) (left axis) and capacity utilization (share of rigs not idle in the North Atlantic area) (right axis). Sources: EIA and Clarksons Platou Offshore



Next, based on the estimated model, we make conditional forecasts of the two endogenous variables over the period 2014q1 to 2016q4. We consider quarterly point estimates for rig rates and capacity utilization for one reference simulation and two sensitivity simulations: A high oil price simulation and a simulation featuring expansion into new Arctic areas in the Barents Sea and the areas around Jan Mayen. We generate forecast intervals for the reference simulation. Here forecast uncertainty stemming from the error terms in the forecast period is assessed by bootstrapping from the in-sample residuals for the reference simulation. Also the point forecasts are based on information from the bootstrapped sample, since we employ the mean over the replicated values.

In the reference simulation, the oil price is roughly halved from 2014q1 to 2016q4. We find that this results in a marked decline in rig rates and capacity utilization over the forecasting horizon. The rig rate is predicted to fall by almost one third whereas the capacity utilization is predicted to decrease by 14 percentage points (from 2013q4 to 2016q4). In the high oil price simulation we keep the oil price constant at the 2014q1 level. As expected from the theory model, the econometric model then forecasts higher rig rates, that is, one third higher at the end of the forecast horizon (2016q4) as compared with the reference simulation. In the sensitivity simulation, we find that the rig rate increases slightly following an opening for petroleum activity in the Barents Sea and around Jan Mayen (relative to the reference simulation).

The empirical literature on rig activities is relatively small, probably because adequate data are scarce. Ringlund *et al.* (2008) find a positive relationship between oilrig activity and the crude oil price, but the strength of the relationship differs across regions. Boyce and Nøstbakken (2011) study exploration and development of oil and gas fields in the U.S. over the period 1955–2002, with focus on Hotelling scarcity effects and technological change. Kellogg (2011) estimates learning-by-doing effects of drilling activity in Texas, and demonstrates the importance of the contracting relationship between oil companies and drilling contractors. Iledare (1995) estimates the effects of gas prices on natural gas drilling in West Virginia for the years 1977–1987. Most closely related to the present paper is Osmundsen *et al.* (2015), who examine the formation of rig rates for jack-ups in the Gulf of Mexico. The econometric approach in the present paper and Osmundsen *et al.* (2015) differs in that the latter utilizes a single equation framework on the micro level and treats capacity utilization (i.e., the supply side) mainly as exogenous. Moreover, Osmundsen *et al.* (2015) do not present any forecasting in their paper.[5]

In Section 2 we present a simple economic model which is used to choose candidate explanatory variables to the econometric model. We develop the econometric model in Section 3 and report estimation results in Section 4. Reference forecasts and results from sensitivity simulations are given in in Section 5. Section 6 concludes.

2. Theoretical background

Rig hire is a contract market. When capacity utilization is low, contract duration is low and contracts are fairly standardized. The market then approaches a spot market, but longer contracts are still prevalent. Thus, both traditional market analysis and bargaining theory may shed light on the rig market. According to our experience, however, the richest implications can be drawn from bargaining theory. Thus, we develop a bargaining model for rig hire and contract terms.

Our point of departure is a negotiation situation between a representative petroleum company, which considers a number of potential drilling projects (e.g., exploration or development drilling), and a representative rig contractor, which owns N rigs. The cost of hiring one rig (denoted i) consists of the rig rate p_i and the contract length q_i; i.e. the daily rental price for rig i and the number of hiring days.

[5] There is also a related literature on empirical studies of oil and gas exploration and development, see e.g. Mohn (2008) and Mohn and Osmundsen (2008) for the Norwegian Continental Shelf, Lin (2009) for the Gulf of Mexico, and Kemp and Kasim (2003) for the UK Continental Shelf.

Let the contract volume q during a certain time period be defined as $q = \sum_i q_i$, i.e., the total number of contracted days, summed over all rigs (note that we may have $q_i = 0$ for several of the rigs). Further, let p denote the (weighted) average rig rate in this period, i.e., $p = \sum_i p_i q_i / q$.[6] In the analysis below, we will consider a negotiation over the two variables q and p.

We apply the standard bargaining solution (see, e.g., Watson, 2002) to solve for the two variables.[7] The standard bargaining solution implies that the players first determine the contract volume q that maximizes their joint value of the agreement ω. Then they share ω based on their relative bargaining power. This implies that q is independent of the rig rate p. Note that any contract that does not maximize ω with respect to q can be renegotiated for a Pareto improvement where both parts are better off.

Let $\mathbf{x}_1$ and $\mathbf{x}_2$ denote vectors of exogenous variables that determine the oil company's profits from drilling and the rig contractor's drilling costs, respectively. The functions $\pi(q, \mathbf{x}_1)$ and $c(q, \mathbf{x}_2)$ then refer to the present values of profits and costs associated with the number of hired rig days q. Let $\tilde{x}_1$ and $\tilde{x}_2$ refer to particular variables in $\mathbf{x}_1$ and $\mathbf{x}_2$, respectively. We assume that $\pi(q, \mathbf{x}_1)$ and $c(q, \mathbf{x}_2)$ are monotonic in all $\tilde{x}_1$ and $\tilde{x}_2$, and to simplify the exposition we define $\mathbf{x}_1$ and $\mathbf{x}_2$ such that $\partial\pi / \partial\tilde{x}_1 \equiv \pi_{\tilde{x}_1}, c_{\tilde{x}_2} > 0$. For example, if capital costs reduce profits and increases costs, we use the negative of capital costs in $\mathbf{x}_1$. We also assume that the cross-derivatives satisfy $\pi_{q\tilde{x}_1} > 0$ and $c_{q\tilde{x}_2} > 0$. In the case of the profit function, this assumption states that an additional hired rig day is more profitable for the oil companies if a variable that increases profits obtains a higher value. For example, the oil company gains more from an additional hired rig day if the oil price increases. The interpretation regarding the cross derivative of the rig operator's cost function is similar.

[6] Alternatively, q and p could be specified as vectors over all q_i and p_i. However, that would complicate the notation below without changing the insight from the analysis.

[7] The standard bargaining solution encompasses the Nash bargaining solution, which can be shown to imply that profits are split equally between rig operators and petroleum companies. The standard bargaining solution also encompasses outcomes where the profits are unevenly split between the two players (cf. the variable θ below).

The variable $\theta\left(q^*\right) \in (0,1)$ denotes the relative bargaining power of the petroleum company.[8] We assume that this decreases with the number of contracted days such that $\theta_q < 0$. One important reason for this is that the petroleum companies' outside options (i.e., the option of hiring a rig from another rig company) increases with the availability of rigs (decreases with the capacity utilization), whereas the opposite tends to be the case for the rig operator which may have more offers to choose from. Furthermore, we assume the oil company prioritizes the most promising projects, so profits increase concavely in *q*. Last, we let rig supply costs increase convexly in *q*, e.g. because of maintenance requirements and use of less suitable rigs as the number of available rigs decreases. For example, it is costly to use a highly advanced semi or drillship for simple operations. More formally we have $\pi_q, c_q, -\pi_{qq}, c_{qq} > 0$, with all derivatives assumed to be finite.

The joint profit of the standard bargaining agreement is:

(1) $$\omega\left(q, \mathbf{x_1}, \mathbf{x_2}\right) \equiv \max_q \left[\pi\left(q, \mathbf{x_1}\right) - c\left(q, \mathbf{x_2}\right)\right].$$

Since joint profit is concave in q, this equation implicitly yields the optimal contract volume q* as characterized by the first order condition $\pi_q\left(q^*, \mathbf{x_1}\right) = c_q\left(q^*, \mathbf{x_2}\right)$ (given $\omega > 0$ which ensures interior solution). The profit share from the agreement accruing to the petroleum company and the rig contractor are, respectively (we henceforth omit the parentheses with exogenous variables in functions to simplify notation):

(2) $$\theta\omega = \pi - pq^* \text{ and } (1-\theta)\omega = pq^* - c$$

Using equations (1) and (2) we get the rig rate (remember *q** is given from (1) and independent of *p** and θ):

(3) $$p^* = \frac{1}{q^*}\left(\pi + \theta\left(c - \pi\right)\right)$$

Equations (1) and (3) solve the bargaining game. Together they imply:

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[8] The condition $\theta \in (0,1)$ ensures that both parts gain some profit from the agreement if $\omega > 0$ (participation constraint). We assume no contract is signed if $\omega \leq 0$.

(4)

$$\frac{dq^*}{d\tilde{x}_1} = \frac{\pi_{q\tilde{x}_1}}{c_{qq} - \pi_{qq}}, \qquad \frac{dq^*}{d\tilde{x}_2} = \frac{c_{q\tilde{x}_2}}{\pi_{qq} - c_{qq}}$$

$$\frac{dp^*}{d\tilde{x}_1} = \frac{1}{q^*}\left(\underbrace{(1-\theta)\pi_{\tilde{x}_1}}_{\text{Direct effect}} + \underbrace{\left(\theta_q^*(c-\pi) + \pi_q - p^*\right)\frac{\partial q^*}{\partial \tilde{x}_1}}_{\text{Indirect effect via change in } q^*} \right), \quad \frac{dp^*}{d\tilde{x}_2} = \frac{1}{q^*}\left(\underbrace{\theta c_{\tilde{x}_2}}_{\text{Direct effect}} + \underbrace{\left(\theta_q^*(c-\pi) + \pi_q - p^*\right)\frac{\partial q^*}{\partial \tilde{x}_2}}_{\text{Indirect effect via change in } q^*} \right)$$

The rig rate *p** depends on *q** (since *q** affects the bargaining power), rig contractor costs and oil company profits. In the following we assume that the direct effect on the rig rate from a change in an exogenous variable, $\pi_{\tilde{x}_1}$ or $\pi_{\tilde{x}_2}$, dominates the indirect effect of these variables via adjustments of *q**. This implies that $dp^* / d\tilde{x}_1, dp^* / d\tilde{x}_2 > 0$ in Eq. (4). We also observe that the rig operator's relative bargaining power, and hence the rig rate, increases if a change in the exogenous variable increases *q**.

We then have the following result:

Lemma 1. *Assume* $\omega > 0$ *so that* $q^* > 0$. *Then we have:*

An increase in oil company profits or a decrease in rig operator costs, caused by a change in $\mathbf{x}_1$ or $\mathbf{x}_2$, *increases the optimal contract volume.*

An increase in oil company profits or rig operator costs, caused by a change in $\mathbf{x}_1$ or $\mathbf{x}_2$, *increases the rig rate.*

Proof. *The lemma follows directly from Eq.* (4).

Table 1 lists some important exogenous variables in $\mathbf{x_1}$ and $\mathbf{x}_2$ along with their probable effects on the oil company profit $\pi(q, \mathbf{x_1})$ and the rig operator cost $c(q, \mathbf{x_2})$. It also shows the implied effects on the rig rate *p** and the contract volume *q** as predicted by Lemma 1. For example, everything else equal, petroleum company profit increases in the oil price. Hence, Lemma 1 indicates that a higher oil price increases the rig rate and the contract volume.

Table 1: Hypothesized direct effects of exogenous variables in the analytical model

Variable	Oil company profit	Rig contractor cost	Rig rate	Contract volume
Oil price	Positive		Positive	Positive
Remaining resource	Positive		Positive	Positive
Capital cost (real interest rate)	Negative	Positive	Ambiguous	Negative
Labor cost (real wage)	Negative	Positive	Ambiguous	Negative
Operation complexity		Positive	Positive	Negative
Oil company favorable regulation	Positive		Positive	Positive

Note: "Oil company favorable regulation" may e.g. include tax exemptions and lax environmental regulation.

Some entries in Table 1 warrant attention. First, several variables affect costs and benefits of the agreement *after* the contract is signed (e.g., oil price and real interest rate). Thus, it is rather the expected future values of these variables that matter. Second, some rig operations are more demanding than others, e.g. because of deep water or harsh climate. This typically increases the rig operation cost, but it seems unreasonable to expect it to induce shorter contract length for a given operation. On the other hand, higher costs due to operational complexity imply that fewer projects are developed as profits net of rig costs decrease.

The econometric model features rig and capacity utilization rates as its two endogenous variables. The capacity utilization rate is the number of hired rig days divided by the number of available rig days. For a given capacity $\overline{q}$, capacity utilization is then equal to $q/\overline{q}$ in the theory model. We therefore expect the theory model's predictions regarding q to apply to the capacity utilization variable (*CAPUT*) in the econometric model.

3. Data, aggregation and modelling framework

Our point of departure is micro data, with floaters as the observational unit. We have to our disposition 540 observations of new contracts signed for the Norwegian continental shelf within a time interval spanning the period from the start of the 1990's to the end of 2013. Table A1 in Appendix A shows the number of observations and the number of observational units behind the means in every period. Note that in some periods the number of observational units is smaller than the number of observations. The reason is that some observational units are represented by more than one observation. The data have been obtained from the shipbroking company Clarksons Platou Offshore, and include information about the daily rig rate for each contract. These rates are in current US$ and we have deflated them by a producer price index to obtain rig rates in constant prices.[9] The data also

[9] We use the producer price index for "Industrial commodities less fuels" from http://www.bls.gov/data/home.htm. The base year is 2010.

include the fixture date, i.e., the date when the contract is signed, as well as the starting and end dates for each contract. Thus, for every contract we can derive both the contract length and the lead time, i.e., the number of days from the fixture date to the start date.[10] The data also include rig-specific information such as the year of construction, maximal drilling depth, and rig classification, see Table 2.[11]

Table 2. Overview of time series variables used for the reference model

Variable	Description	Type of underlying variable	Source	Denomination
rigrate	Mean of log rig rates in constant prices	Varies across observational unit and time	Clarksons Platou Offshore	USD (2010) per day
OILPRICE	Oil price at constant prices	Time series from the outset	EIA	US $ per barrel in fixed 2010-prices
CAPUT	Capacity utilization	Time series from the outset	Clarksons Platou Offshore	0<=CAPUT<=1
remres	Log of remaining reserves	Time series from the outset	Norwegian Petroleum Directorate	REMRES measured in Million standard cubic meter o. e.
RIR	Real interest rate	Time series from the outset	OECD Economic outlook	Annual rate in %
LEADTIME	Mean of lead times	Varies across observational unit and time	Clarksons Platou Offshore	No. of days
depth	Mean of log maximal drilling depths	Time invariant characteristic	Clarksons Platou Offshore	DEPTH measured in feet
SHARE4[a]	Share of rig type 4	Time invariant characteristic	Clarksons Platou Offshore	0<=SHARE4<=1
SHARE5[a]	Share of rig type 5	Time invariant characteristic	Clarksons Platou Offshore	0<=SHARE5<=1
SEAS2	Seasonal dummy for the second quarter	Time series from the outset		
T1	Step dummy	Time series from the outset		1 until and including 1995q3, thereafter 0

[a]*SHARE*4 and *SHARE*5 denote the share of contracts signed within a given quarter applying to rigs belonging to classes 'SEMI 2. GEN' and 'SEMI 3. GEN', respectively. See http://petrowiki.org/History_of_offshore_drilling_units for information about rig class specifications.

In our estimations (and forecasts) we implicitly consider the NCS as a separate market for floaters. One motivation for this is that the number of rigs operating on the NCS is, at least in the short run,

[10] The contract length, *CONLENGTH*, has been included in the empirical analysis, but is not included in the reference model . However, it is included in one of the alternative models in Appendix B.

[11] There are three main rig types operating on the NCS: Jack-ups, semisubmersibles (of different generations), and drillships. The two latter categories are floaters. On the NCS, jack-ups rarely operate on water depths exceeding 130 meters. Semi-submersible rigs are moored to the sea floor and obtain buoyancy from ballasted pontoons located below the ocean surface. Drillships are specialized ships with drilling equipment. They are expensive but very mobile. The choice of rig type depends on the characteristics of the particular drilling operation. For more information, see e.g. Kaiser and Snyder (2013, Chap. 1.2).

little responsive to rig demand. Moving rigs over long distances is costly, especially for semisubmersibles.[12] Further, strict Norwegian regulations may impede rig relocation from e.g. the UK Continental Shelf to the NCS, due to additional costs related to e.g. upgrading of living quarters, lifting mechanisms, lighting and noise (Ministry of Petroleum and Energy, 2012). In the longer run, however, the Norwegian rig market is likely to be somewhat influenced by other rig markets, especially in the North Atlantic area. Moreover, from the data provided by Clarksons Platou Offshore we have employed a variable for the capacity utilisation for floaters in the whole North Atlantic area. Thus, our capacity utilization measure should be considered as a proxy for the capacity utilization on the NCS. The utilization rate, which is then equal for all observations from the same time period, shows considerable variation over the sample period (see Figure 2).

For the oil price we use the monthly Brent Blend price taken from the EIA (see Figure 2).[13] These prices are deflated by the same price index as used for the rig rates. We assume that oil companies' price expectations are adaptive, meaning that their price expectations are continually updated based on current and previous prices (see e.g., Farzin, 2001, Nguyen and Nabney, 2010, Aune et al., 2010, and Osmundsen et al., 2015). Thus, we construct smoothed oil prices that are weighted averages of current and historic prices. The smoothed oil price in period *s* ($SOILPRICE_s$) is then assumed to follow a Koyck lag structure, see Koyck (1954):

$$SOILPRICE_s(\alpha) = \alpha \sum_{j=0}^{T} (1-\alpha)^j OILPRICE_{s-j},$$

where $OILPRICE_s$ is the real price of oil in period *s*.[14]

Annual time series for remaining reserves (*REMRES*) refer to petroleum resources that are expected to be profitable to extract given current and expected economic conditions, and where plans for development and operation of the petroleum deposits are either approved or submitted to the

[12] According to the Ministry of Petroleum and Energy (2012), semisubmersibles accounted for 22 out of 23 floaters operating on the NCS by late December 2011 – the last one being a drillship.

[13] http://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm. For the period before 1987 we employ a monthly time series for the Brent Blend oil price provided by the Central Bank of Norway.

[14] In principle, the sum should include price levels even longer back than *T* periods. However, we use *T*=47, which means that we use a filter spanning 12 years. Note that when *T* goes to infinity the sum of the weights equals 1 for all feasible values of α. As will be seen later, in the empirical part of the paper, our estimate of α implies that the estimate of the sum $\alpha\sum_{j=0}^{T}(1-\alpha)^j$ is very close to unity. We have therefore not modified the weights such that the sum of the estimated weights is exactly equal to unity. This has no implications from a practical point of view.

government. The time series for this variable have been obtained from the Norwegian Petroleum Directorate.[15]

From these data we construct quarterly time series by aggregation. The first period is 1991q4 and the last period is 2013q4. The same observational unit is not observed in each quarter and it is also common that one has more than one observation for an observational unit in some time periods. The number of micro observations on which the quarterly observations are based varies from 1 to 24. For a single quarter, i.e. 2008q4, there are no observations. Thus our time series contain one missing observation. Our subsequent empirical analysis is based on these aggregate data together with variables that are time series from the outset, such as the oil price.

Our micro dataset contains three variables that vary both across observational units and over time. This is the rig rate in constant prices (*RIGRATE*), the length of the contract (*CONLENGTH*) and the lead time associated with the contract (*LEADTIME*). For the rig rate we log-transform the data and obtain the variable *rigrate* = log(*RIGRATE*). The variables *rigrate, CONLENGTH* and *LEADTIME* are aggregated in the same manner, and below we show how the aggregation is carried out for *rigrate*. Let $rigrate_{it_i(s)}$ denote the *t*'th observation on the log of rig rates for rig *i* in period s. Let *I(s)* denote a set consisting of the rigs present in period *s*. Let $t_i(s)$ take on the values $1_i(s)$ to $N_i(s)$. The un-weighted mean of the values from period *s* is then given by

$$rigrate_s = \frac{1}{\sum_{i \in I(s)} N_i(s)} \sum_{i \in I(s)} \sum_{t_i(s)=1_i(s)}^{N_i(s)} rigrate_{it_i(s)}.$$

The micro data set we apply contains several rig specific characteristics, i.e. variables that are time invariant and only vary across different observational units. The different characteristics are indicated in Table 2. One of these variables is the maximal drilling depth, *DEPTH*. As for the rig rates, we consider the log-transformed variable, *depth*=log(*DEPTH*). The corresponding aggregate variable is defined as

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[15] Estimates for remaining resources are retrieved from yearly publications over the period 1990 to 2014, named "Facts 1990",…,"Facts 2014", see http://www.npd.no/en/Publications/Facts/. The variable *REMRES* and the two companion variables *POT* and *REMREC* (See Table B3 in Appendix B) are all annual variables from the outset. They have been converted to quarterly time series in a technical way by using the convert option in TSP 5.0, cf. Hall and Cummins (2005, pp. 99-101).

$$depth_s = \frac{1}{\sum_{i \in I(s)} N_i(s)} \sum_{i \in I(s)} N_i(s)\, depth_i$$

Time series for the other time invariant variables are obtained in a similar manner.[16]

As mentioned above, some of the variables are time series from the outset. This is the case for the oil price (*OILPRICE*) and the capacity utilization rate (*CAPUT*). We have also included a step dummy labelled *T1* in the data set.[17] In the following we formulate an econometric reduced form model with $rigrate_s$ and $CAPUT_s$ as the two modelled variables. [18]

(5)
$$rigrate_s = \mu_1 + \phi_1 \times RIR_{s-1} + \beta_1 \times \log\left[\sum_{j=0}^{47} \alpha(1-\alpha)^j OILPRICE_{s-j}\right] + \eta_1 \times remres_{s-1} + \\ +\delta_1 \exp(CAPUT_{s-1}) + \zeta_1 \times LEADTIME_s + \kappa_{15} \times SHARE5_s + \pi_1 \times T1_s + \varepsilon_{1s},$$

(6)
$$\log\left(\frac{CAPUT_s}{1-CAPUT_s}\right) = \mu_2 + \eta_2 \times remres_{s-1} + \delta_2 \times \log\left(\frac{CAPUT_{s-1}}{1-CAPUT_{s-1}}\right). \\ +\kappa_{24} \times SHARE4_s + \omega_2 \times ldepth_s + \nu_2 \times SEAS2_s + \varepsilon_{2s}$$

We assume that $\varepsilon_s = [\varepsilon_{1s}, \varepsilon_{2s}]'$ follows a white noise process. Note that Eq. (6) implies

(7)
$$CAPUT_s = \frac{\exp(X_s)}{1+\exp(X_s)},$$

with

$$X_s = \mu_2 + \eta_2 \times remres_{s-1} + \delta_2 \times \log\left(\frac{CAPUT_{s-1}}{1-CAPUT_{s-1}}\right) + \\ \kappa_{24} \times SHARE4_s + \omega_2 \times depth_s + \nu_2 \times SEAS2_s + \varepsilon_{2s} \quad .$$

---

[16] Note that if the data had been balanced panel data, $depth_s$ would have been a constant.

[17] We find it hard to give this variable an interpretation, but it has been included since it seems to generate marginal effects of other variables that are more realistic than those obtained when it is omitted.

[18] In a part of the observation points the capacity utilization equals 1. In these cases we have imputed the value 0.99621, which corresponds to the mean of the value 1 and the highest observed capacity utilization strictly below 1.

Eq. (7) will be utilized later for forecasting purposes. We observe that the capacity utilization rate is included in the rig rate equation, whereas the rig rate is not included in the equation for the capacity utilization. This is consistent with the theoretical model, and is also consistent with our estimation of all the alternative models, but one.

4. Estimation results

Reference model

The non-linear multivariate regression estimates of the reference model are provided in Table 3 below.[19] Most of the parameter estimates in Table 3 are significant at the five percent level. The log of the smoothed oil price only enters positively in the reduced form equation of the (log) rig rate with a parameter estimate of 0.78, cf. the estimate of β_1. The estimate of the smoothing parameter, α, is 0.11. This parameter weighs the importance of oil prices from different points of time. The estimate on 0.11 suggests that the expectations about future oil prices are updated quite fast to new oil price observations. For example, the oil price three years ago weighs roughly one quarter of the present oil price in the Koyck lag specification. We observe that the oil price only enters the rig rate equation.

Also the lagged real interest rate impacts the rig rate positively, cf. the estimate of ϕ_1 in Table 3. A one percentage point increase in the lagged real interest rate leads to a 0.078 increase in the log rig rate. In the theory model we found that the real interest rate has an ambiguous effect on the rig rate (cf. Table 1). The reason is that the real interest rate increases the capital cost of oil companies, making them less willing to pay for rigs, and increases the rig contractors' capital costs and hence the cost of supplying rigs. The positive estimate suggests that the rig contractor capital cost effect dominates in the period 1990-2014 in the NCS.

The lagged (antilog transformed) capacity utilization rate, i.e., $\exp\left(CAPUT_{s-1}\right)$ is yet another variable that has a positive impact on the rig rate, cf. the estimate of δ_1.[20] This is as expected, because higher capacity utilization increases both the bargaining power of the rig contractors and the cost of supplying rigs (e.g., because of maintenance requirements). The same is true for the lagged lead time variable, cf. the estimate of ζ_1. We observe that a longer lead time suggests more pressure in the rig market, and thus has similar effects on the rig rate as capacity utilization.

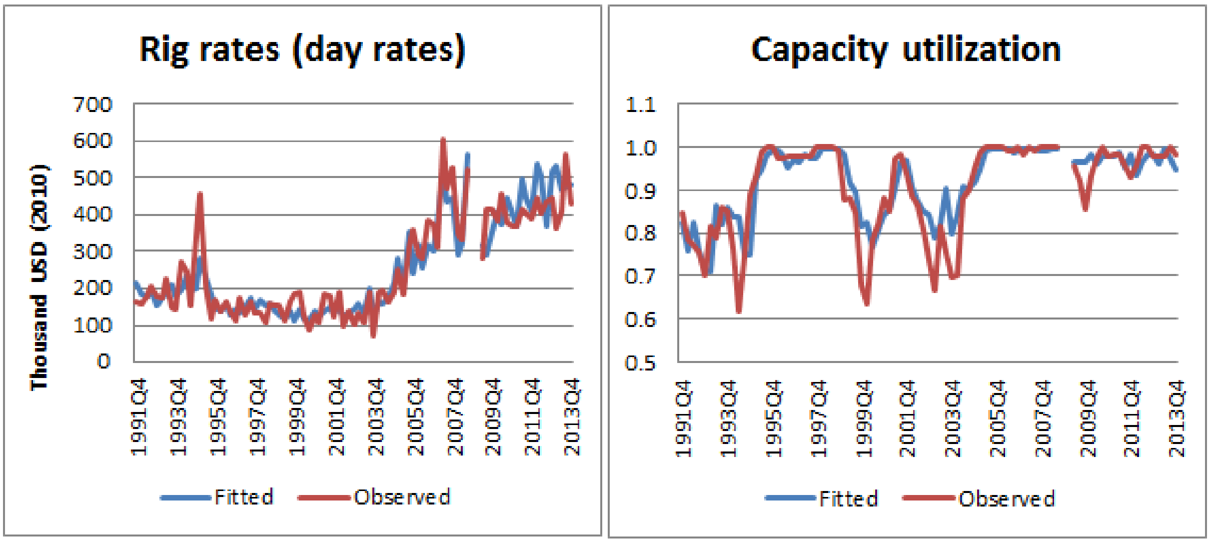
[19] All the numerical calculations have been carried out using TSP 5.0, cf. Hall and Cummins (2005).

[20] The reason for using the antilog transformation is that we a priori believe that the effect of an increase in the capacity utilization is stronger the higher the capacity utilization is.

We also find a significant positive effect of the lagged stock of remaining petroleum reserves (log-transformed), cf. the estimate of the parameter η_1. Intuitively, more available resources imply larger profit potential for the oil companies, and hence increased rig demand. Finally a rig classification variable and a step dummy are also present in the reduced form equation of the (log) rig rate, cf. the estimates of the two parameters κ_{15} and π_1. This reflects that rig characteristics differ across rigs, e.g. with respect to rental costs and services the rig can supply.

The most significant variable in the reduced form equation of transformed capacity utilization is the lagged left-hand side variable, which enters with an estimate of 0.81, cf. the estimate of δ_2 in Table 3. Thus, there is a high degree of persistence. Another significant variable is the (log) maximal drilling depth, *depth*, which enters positively and with an estimate that is not far from unity, cf. the estimate of ω_2. We have also included the log of remaining petroleum reserves lagged one quarter, i.e., $remres_{s-1}$, in the capacity utilization equation, even though it does not enter significantly, cf. the estimate of the parameter η_2 and the corresponding *t*-value. Since it enters with the correct sign we have decided to retain the variable in the capacity utilization equation because of the theoretical considerations. One of the alternative simulations in the forecast part of this paper is related to an alternative path for this variable. Also two other variables have a positive effect, a rig classification variable and a seasonal dummy for the second quarter of the calendar year, cf. the estimates of κ_{24} and ν_2, respectively. In the last part of Table 3 some diagnostics for the two equations are reported. The model seems reasonably well-specified. There are no signs of heteroskedasticity. The DW-statistics are in the area of 1.6-2.0. Figure 3 shows the reference model's within-sample fit for the two endogenous variables.

Figure 3. Model fitted and observed endogenous variables



In Appendix B we report results for some other model specifications obtained by extending or modifying the reference model with respect to exogenous variables used as regressors. Altogether there are 11 such models. Model 6, which features a dummy variable for the petroleum tax relief in 2005, is of particular interest, suggesting that the Norwegian government policy to spur activity on the NCS has worked as intended.

Table 3. Non-linear multivariate regression estimates

Parameter	Related variable etc.	Estimate	*t*-value
Rig rate Eq. (5)			
μ_1	Constant	4.850	2.701
ϕ_1	$remres_{s-1}$	0.469	2.194
η_1	RIR_{s-1}	0.079	3.009
α	Smoothing parameter	0.110	2.135
β_1	$soilprice_s^a$	0.780	9.270
δ_1	$\exp(CAPUT_{s-1})$	0.235	2.013
ς_1	$LEADTIME_{s-1}/100$	0.061	2.897
κ_{15}	$SHARE5_s$	-0.416	-4.258
π_1	$T1$	0.336	3.762
Capacity utilization Eq. (6)			
μ_2	Constant	-14.050	-2.460
η_2	$remres_{s-1}$	0.938	1.299
δ_2	$\log(CAPUT_{s-1}/(1-CAPUT_{s-1}))$	0.811	15.174
κ_{24}	$SHARE4_s$	0.736	1.950
ω_2	$depth_s$	0.894	3.456
υ_2	$SEAS2_s$	0.441	2.257
Diagnostics:			
Number of observations		87	
Sample period		1991q4-2013q4[b]	
R^2 Eq. (5)		0.836	
DW Eq. (5)		1.808	
LM-test for heteroskedasticity (*p*-value) Eq. (5)		0.183	
R^2 Eq. (6)		0.785	
DW Eq. (6)		1.646	
LM-test for heteroskedasticity (*p*-value) Eq. (6)		0.183	

[a] $soilprice_s = \log\left[\sum_{j=0}^{47} \hat{\alpha}\left(1-\hat{\alpha}\right)^j \times OILPRICE_{s-j}\right]$.

[b] The data cover the period 1991q4-2013q4 except for 2008q4 and 2009q1.

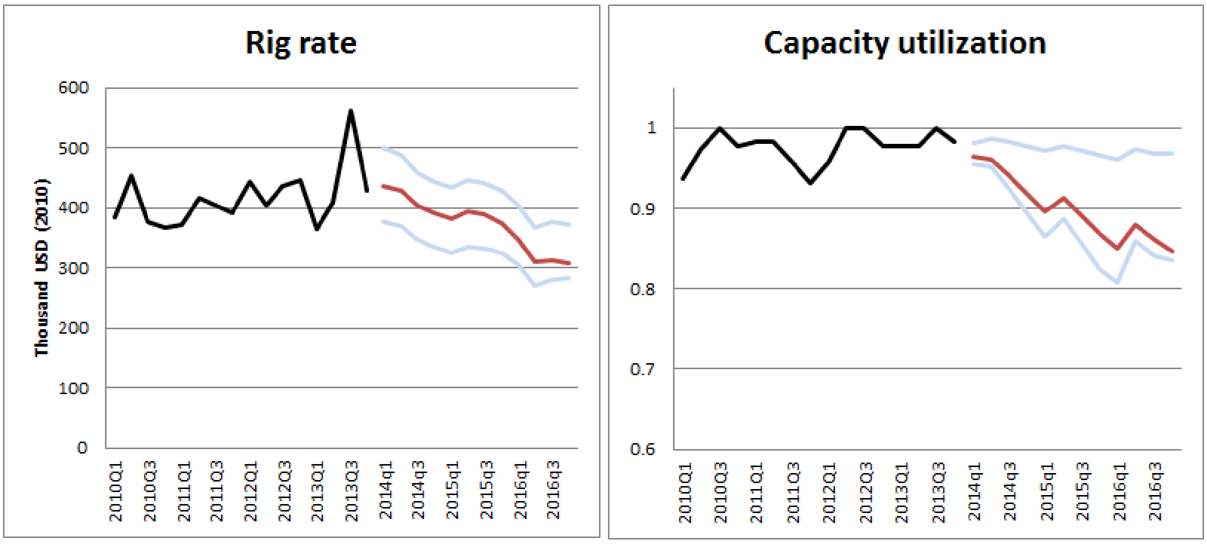
5. Forecasts and forecast uncertainty of the rig rate and the capacity utilization rate

In this part of the paper we present conditional forecasts for the period 2014q1-2016q4 using the reference model. We distinguish between a reference simulation and two alternative simulations, which we label, respectively, "Higher oil price" and "Larger reserves". Appendix C contains information on what have been assumed for the exogenous variables for the simulation period 2014q1-2016q4. For all the three simulations we report point forecasts, whereas we for the reference simulation also consider forecast uncertainty stemming from the errors. In Appendix D we give an account of how the forecast uncertainty is calculated by a bootstrap approach.[21] Our point forecasts are also based on results from the bootstrap procedure. We employ the mean forecasts across the replications. An argument for this is that the econometric model is formulated in transformed variables, whereas we focus on forecasting the untransformed variables.

In Figure 4 we show the point forecasts of *RIGRATE* and *CAPUT* obtained in the reference simulation together with the implied forecast uncertainty. The assumptions with respect to the exogenous variables used in conjunction with the reference simulation are given in Table C1 in Appendix C and the involved parameter estimates are those reported in Table 3. According to the reference simulation, both the rig rate, *RIGRATE*, and the capacity utilization, *CAPUT*, are predicted to fall from the beginning of 2014 to the end of 2016. The rig rate is predicted to fall by 28 percent whereas the capacity utilization is predicted to decrease by 14 percentage points (from 2013q4 to 2016q4). A major factor behind this drop in the rig rate is the substantial fall in the oil price (in constant prices), even if this fall is somewhat dampened since we use a smoothed oil price as an explanatory variable. As seen from the second column of Table C1 in Appendix C, the oil price in fixed prices is more than halved from the start of 2014 to the end of 2015 and is assumed to increase only moderately during 2016. The oil price observations in the period 2014q1 to 2015q2 correspond to observed values, while for the remaining period we have made assumptions in the light of the development of future prices. The estimated capacity utilization equation is dominated by an autoregressive slope coefficient somewhat below unity. This feature contributes to a reduction in the capacity utilization during the forecast period, which gives negative impulses to the rig rate.

[21] For bootstrap methods for time series see Kreiss and Lahiri (2012).

Figure 4. Forecasts of rig rates and capacity utilization in the reference simulation, including 50% forecast intervals. See Table C3 and Table C4 in Appendix C for the basis of the figures



In Figure 4 we report 50% forecast intervals for the values of the two endogenous variables, i.e., $RIGRATE_s$ and $CAPUT_s$ in the period 2014q1-2016q4.[22] The forecasts intervals account for uncertainty stemming from the errors of the two equations.[23] How the forecast intervals have been calculated is outlined in Appendix D. The forecast intervals for the rig rate are rather wide. In 2016q4, the last quarter that we consider, the calculated forecast interval of the rig rate starts at 282 thousand USD per day and ends at 373 thousand. The corresponding values for the capacity utilization are 0.84 and 0.97. If one looks at the ratios between the length of the forecast interval and the point forecast, they increase moderately for the rig rate over time, whereas there is a larger increase for the capacity utilization rate. The reason for this feature is that there is no lagged rig rate involved in the reference model, and that the estimated slope parameter of the lagged transformed capacity utilization variable in the rig rate equation, i.e., exp($CAPUT_{s-1}$), is relatively moderate in size, dampening the contribution of lagged errors in the capacity utilization equation to the forecast errors of the rig rate equation.

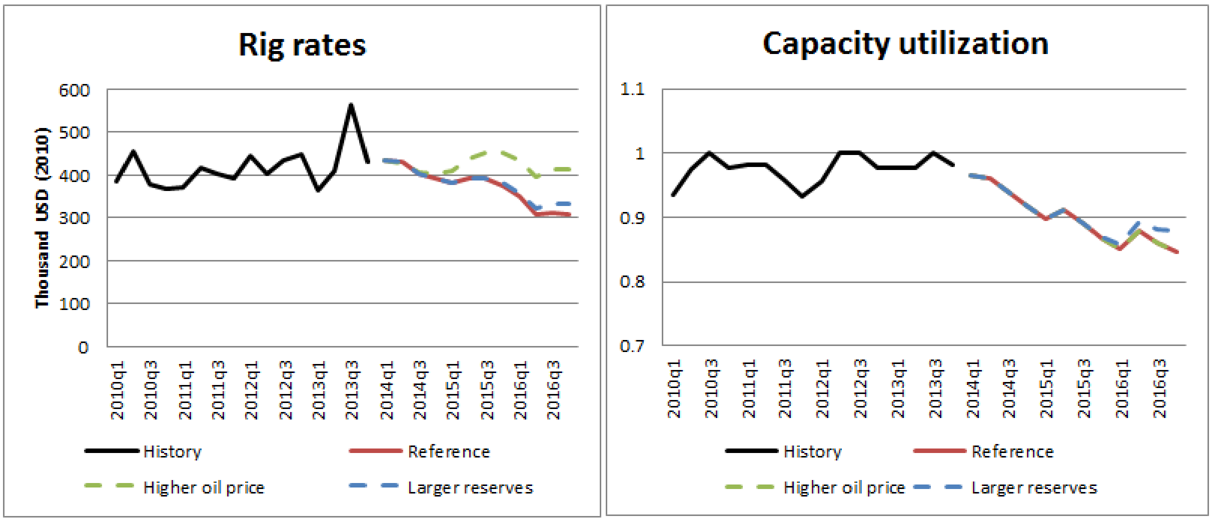
In Figure 5 we show the point forecasts based on the reference models together with the forecasts under the two alternative simulations, *Higher oil price* and *Larger reserves*. In the *Higher oil price* simulation we assume another, partly counterfactual, path of the oil price by setting it to 100 USD per

[22] Granger (1996) suggested that a 50 percent forecast interval tends to be more interesting from a practical point of view compared to a 90 percent interval since the latter commonly yields a rather wide interval.

[23] Note that the forecast intervals are asymmetric around the point forecasts. This feature follows from how the intervals are calculated. As explained in Appendix D, the lower and upper levels of the intervals correspond to the first and third quartiles in the distributions of replicated forecasts. Since the distributions are skew the mean of the distributions deviates from median value.

barrel (in constant prices) for the entire period 2014q1-2016q4, i.e., close to the price at the beginning of the forecast period. Accordingly, the rig rate shows only a slight reduction from 2014q1-2016q4. As we noted earlier, the capacity utilization does not depend on the oil price, which implies that the capacity utilization path is the same for the reference simulation and the higher oil price simulation. In the *Larger reserves* simulation we are looking at the implications on the NCS rig market following opening for petroleum activity in the Barents Sea and areas around Jan Mayen. The associated increase in petroleum reserves is 12.3 percent, relative to the reference simulation. However, since this variable enters with a lag, we see from tables C1 and C2 in Appendix C that it is not until 2015q4 that the *Larger reserves* deviates from the reference simulation. The petroleum reserve variable, *remres*, impacts both the rig rate and the capacity utilization variables positively. This is the reason why the reduction in the rig rate from 2014q1 to 2016q4 is less than in the reference simulation. However, the large decrease in the petroleum price also dominates in this case, giving a reduction in the rig rate from 2013q4 to 2016q4 of 23 percent. The capacity utilization decreases less in this simulation than in the reference simulation since an increase in the petroleum reserves gives positive impulse to the capacity utilization.

Figure 5. Forecasts of rig rates and capacity utilization in the reference simulation and in the *Higher oil price* and *Larger reserves* simulations. See Table C3 in Appendix C for the basis of the graphs



6. Concluding remarks

In this paper we first presented a simple theoretical model to sharpen our understanding of rig markets and help identify the most important drivers for rig rate formation. Then we estimated their effects in the NCS rig market for floaters, using a reduced form two-equation time series econometric model for rig rates and a proxy for capacity utilization over the period 1991q4 to 2013q4. Last, we presented point and interval forecasts for rig rates on the NCS and capacity utilization in the North Atlantic area in a reference simulation and point forecasts for two alternative simulations. The first alternative simulation featured a relatively high oil price (constant at 2014q1 level), and the second involved opening for petroleum activity in new areas.

The results from our econometric analysis of rig rate formation and utilization rates at the NCS are roughly in line with the hypothesized effects from the theoretical model (compare Table 1 with Table 3). Based on the assumption of adaptive oil price expectations according to the Koyck lag structure, we found that expectations about future oil prices are updated quite fast to new oil price observations. In particular, higher oil prices stimulate petroleum development projects. The rig rates then increase because rig operators capture a share of the profitability from petroleum activity, and because higher rig demand induces higher capacity utilization, which again increases the rig operators' relative bargaining strength. On the other hand, we were not able to find a significant positive effect on capacity utilization from higher oil prices. Possible explanations are the highly persistent nature of capacity utilization, and that the endogenous capacity variable *CAPUT* is a proxy variable, since it covers a wider area than the NCS. Because *CAPUT* shows very strong persistence, this is not very problematic with respect to forecasting, given the relatively short forecasting horizon we consider (three years). We found some evidence that increased remaining petroleum reserves stimulate demand for rigs, and hence rig rates and capacity utilization. Lastly, we found significant effects of two rig classification variables and maximum drilling depth. These are again roughly in line with the theory.

The oil price is roughly halved from 2013q4 to 2016q4 in our reference simulation, causing a substantial decline in rig rates and capacity utilization over the forecasting horizon. The rig rate is predicted to fall by 28 percent, whereas the capacity utilization is predicted to decrease by 14 percentage points (from 2013q4 to 2016q4). In contrast, the rig rate remains roughly at the same level in the high oil price simulation, where the oil price is constant at the 2014q1 level. Capacity utilization declines in this simulation too, however. In the second alternative simulation we analyzed effects on the NCS rig market following opening for petroleum activity in the Barents Sea and around Jan Mayen. As expected, this induced higher rig rates and capacity utilization, as compared with the reference simulation. Both rig rates and capacity utilization decline over time in this simulation too, because the sharp decline in the oil price dominates the effect from increased petroleum reserves.

The empirical model in this paper applies to the NCS. Nevertheless, it seems reasonable to expect that many of the variables recognized in this study will also be important constituents of rig rates in other geographical areas where off-shore drilling is applied, in particular as deepwater reserves become more important.

References

Aune, F.R., K. Mohn, P. Osmundsen and K.E. Rosendahl (2010): Financial market pressure, tacit collusion and oil price formation. *Energy Economics* 32 (2), 389–398.

Boyce, J. R. and L. Nøstbakken (2011): Exploration and development of U.S. oil and gas fields, 1955–2002. *Journal of Economic Dynamics and Control* 35 (6), 891–908.

BP (2015): BP Statistical Review of World Energy June 2015, BP. http://www.bp.com/statisticalreview

Corts, K.S. (2008): Stacking the deck: idling and reactivation of capacity in offshore drilling. *Journal of Economic Management and Strategy* 17 (2), 271–294.

EIA (2011): Annual Energy Review 2010. US Energy Information Administration, October 2011.

Hall, B.H. and C. Cummins (2005): *TSP 5.0 Reference Manual*. TSP international.

Farzin, Y.H. (2001): The impact of oil prices on additions to US proven reserves. *Resource and Energy Economics* 23 (3), 271–291.

Granger, C.W.J. (1996): Can We Improve the Perceived Quality of Economic Forecasts? *Journal of Applied Econometrics*, 11 (5), 455–473.

Iledare, O.O. (1995): Simulating the effect of economic and policy incentives on natural gas drilling and gross reserve additions. *Resource and Energy Economics* 17 (3), 261–279.

Kaiser, M.J. and B.F. Snyder (2013): *The Offshore Drilling Industry and Rig Construction in the Gulf of Mexico.* Springer Science & Business Media.

Kellogg, R. (2011): Learning by drilling: interfirm learning and relationship persistence in the Texas oilpatch. *Quarterly Journal of Economics* 126 (4), 1961–2004.

Kemp, A. and S. Kasim (2003): An Econometric Model of Oil and Gas Exploration Development and Production in the UK Continental Shelf: A Systems Approach. *The Energy Journal* 24 (2), 113–141.

Koyck, L.M. (1954): *Distributed Lags and Investment Analysis*. North-Holland, Amsterdam.

Kreiss, J.-P. and S.N. Lahiri (2012): Bootstrap Methods for Time Series. Chapter 1 in Rao, T.S., Rao, S.S. and C.R. Rao (Eds.): *Handbook of Statistics. Volume 30. Time Series Analysis: Methods and Applications.* North-Holland, Amsterdam, pp. 3–26.

Lin, C. (2009): Estimating strategic interactions in petroleum exploration. *Energy Economics* 31 (4), 586–594.

Ministry of Petroleum and Energy (2012): An industry for the future – Norway's petroleum activities — Meld. St. 28 (2010–2011) Report to the Storting (white paper). Ministry of Petroleum and Energy, August 2012. Available at: https://www.regjeringen.no/en/dokumenter/meld.-st.-28-20102011/id649699/

Mohn, K. (2008): Efforts and efficiency in oil exploration: a vector error-correction approach. *The Energy Journal* 29 (4), 53–78.

Mohn, K. and P. Osmundsen (2008): Exploration economics in a regulated petroleum province: the case of the Norwegian continental shelf. *Energy Economics* 30 (2), 303–320.

Nguyen, H.T. and I.T. Nabney (2010): Short-term electricity demand and gas price forecasts using wavelet transforms and adaptive models. *Energy* 35 (9), 3674–3685.

Norwegian Petroleum Directorate (2014): Facts 2014. Norwegian Petroleum Directorate, 2014. Available at: http://www.npd.no/en/Publications/Facts/

Osmundsen, P., Roll, K. H. and R. Tveterås (2010a): Exploration drilling productivity at the Norwegian shelf. *Journal of Petroleum Science and Engineering* 73 (1-2), 122–128.

Osmundsen, P., Roll, K. H. and R. Tveterås (2010b): Drilling speed - the relevance of experience. *Energy Economics* 34 (3), 786–794.

Osmundsen, P., K. E. Rosendahl and T. Skjerpen (2015): Understanding rig rate formation in the Gulf of Mexico. *Energy Economics* 49, 430–439.

Ringlund, G. B., K. E. Rosendahl and T. Skjerpen (2008): Does oilrig activity react to oil price changes? An empirical investigation. *Energy Economics* 30 (2), 371–396.

Seber, G.A.F. and C.J. Wild (1989): *Nonlinear regression*. John Wiley & Son.

Watson, J. (2002): *Strategy: an introduction to game theory.* W. W. Norton & Company.

Appendix A. Information related to the micro data source

Table A1. Number of micro observations behind the aggregate data in each time period

Period	No. of micro obs.	No. of rigs N(s)	Period	No. of micro obs.	No. of rigs	Period	No. of micro obs.	No. of rigs
1990q4	2	2	1999q1	5	5	2007q2	4	2
1991q1	1	1	1999q2	11	7	2007q3	9	3
1991q2	2	2	1999q3	10	8	2007q4	3	3
1991q3	4	4	1999q4	6	6	2008q1	8	4
1991q4	10	10	2000q1	8	6	2008q2	6	4
1992q1	4	4	2000q2	15	8	2008q3	3	1
1992q2	4	4	2000q3	5	4	2008q4	0	0
1992q3	6	5	2000q4	10	9	2009q1	4	3
1992q4	2	2	2001q1	8	6	2009q2	1	1
1993q1	4	4	2001q2	11	7	2009q3	3	3
1993q2	5	5	2001q3	10	6	2009q4	5	4
1993q3	6	6	2001q4	5	4	2010q1	2	2
1993q4	4	4	2002q1	2	2	2010q2	6	4
1994q1	2	2	2002q2	1	1	2010q3	3	3
1994q2	1	1	2002q3	5	5	2010q4	7	5
1994q3	6	5	2002q4	10	7	2011q1	3	3
1994q4	2	2	2003q1	9	6	2011q2	3	3
1995q1	2	1	2003q2	2	2	2011q3	7	6
1995q2	5	4	2003q3	2	2	2011q4	2	2
1995q3	5	4	2003q4	3	2	2012q1	5	5
1995q4	6	5	2004q1	16	8	2012q2	4	4
1996q1	6	6	2004q2	9	5	2012q3	3	3
1996q2	5	4	2004q3	2	2	2012q4	5	5
1996q3	6	5	2004q4	6	6	2013q1	1	1
1996q4	7	4	2005q1	24	6	2013q2	1	1
1997q1	11	10	2005q2	7	3	2013q3	3	3
1997q2	5	5	2005q3	15	7	2013q4	2	2
1997q3	5	4	2005q4	12	5			
1997q4	7	4	2006q1	7	5			
1998q1	7	5	2006q2	14	6			
1998q2	5	5	2006q3	9	5			
1998q3	5	3	2006q4	11	8			
1998q4	6	6	2007Q1	9	6			

Appendix B. Alternative econometric model structures

In this appendix we show the estimation results from alternative model structures. Whereas estimates of the unknown parameters are reported in Table B1, some diagnostics for the residuals are reported in Table B2. The other models are obtained by extending or modifying the reference model in different ways. An overview of additional variables involved when estimating these models is given in Table B3. Altogether there are 11 additional models, and we label them Model 1-Model 11. In Model 1 we allow the log of the smoothed oil price to enter also the capacity utilization equation. The significance of the estimate turns out to be very low. In Model 2 we add the log of the rig rate lagged one quarter. The estimate of the attached coefficient is, as expected, positive, but insignificant at the 5 percent level. It seems that the estimates of the other parameters are qualitatively very equal to the ones obtained for the reference model. In Model 3 we allow the log rig rate lagged one period to enter both equations. The estimates of the two coefficients attached to this additional variable are positive, but insignificant. Again the estimates of the other parameters are little influenced, as the coefficient estimates are rather equal to those obtained for the reference model.

Models 4-6 are all concerned with policy changes. In each case the policy change is represented by a step dummy. The step-dummies are zero before the policy changes are carried out and thereafter equal to unity. All the policy changes are expected to have a positive effect on both the rig rate and the capacity utilization. In Model 4 we add a variable, *DUM1999*, representing changes in the routines related to allocation of licenses through the establishment of the so-called North Sea Awards (NSA) scheme, which developed in 2003 into the Awards in Predefined Areas (APA) scheme. The aim was to increase activity in mature areas. Both the estimate of the parameter attached to this variable in the rig rate equation and the estimate attached to this variable in the capacity utilization equation are insignificant at the 5 per cent significance level. The estimate of the parameter in the rig rate equation is positive, whereas the estimate of the parameter in the capacity utilization equation is negative, which is in contrast to what was expected. Next, in Model 5 we add a step-dummy, *DUM2000*, related to prequalifying of operators and licensees. This aimed to make it simpler for a new company to secure access to acreage, either through license awards or through buying/swopping license interests. The estimates of two parameters attached to this policy variable are negative and insignificant. The third policy variable, *DUM2005*, is allowed to enter in Model 6. This variable represents a petroleum tax relief, giving companies with a tax loss the right to annual refunding of the tax value (78 per cent) of exploration costs. Alternatively, such losses can be carried forward as a tax deduction in later years with an interest supplement. The variable enters with the expected sign in both equations, and in the rig rate equation the estimate is close to be being significant at the 5 per cent level.

In Model 7 the lagged real interest rate, RIR_{s-1}, is also allowed to enter the capacity utilization equation. A negative and insignificant estimate is obtained. In Model 8 we consider the effect of the mean building year, *BUILD*. This variable picks up technological improvement over time. It enters positively in both equations, but only significantly so in the rig rate equation. The estimates of the other parameters are, at least qualitatively, rather equal to the estimates obtained for the reference model.

In Model 9 the contract length, $CONLENGTH_s$, is added to the rig rate equation. A positive and marginal significant estimated effect is obtained. From a qualitative point of view the model share the properties of the reference model, but there are some numerical differences. The point estimates of the adjustment parameter and the parameter attached to $LEADTIME_{s-1}$ are, e.g., somewhat larger in Model 9 than in the reference model.

Whereas Model1-Model9 all are extension of the reference model, Model 10 and Model 11 are modifications of the reference model. In Model 10 the variable for remaining resources, $remres_{s-1}$, is replaced by a variable representing the log of total production potential minus accumulated production lagged one quarter, which we label pot_{t-1} and in Model 11 by a variable for the log of remaining resources lagged one quarter, which we have dubbed $remrec_{s-1}$. None of these variables enter significantly in any of the equations. All the four *t*-values are well below unity in absolute value.

Table B1. Non-linear multivariate regression estimates of additional models[a]

Variable etc.	Eq	Reference model		Model 1		Model 2		Model 3	
		Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.
Constant	(5)	4.850	2.701	4.847	2.697	4.631	2.648	4.628	2.646
$rigrate_{s-1}$	(5)					0.101	1.108	0.101	1.114
$remres_{s-1}$	(5)	0.469	2.194	0.470	2.194	0.400	1.852	0.400	1.850
RIR_{s-1}	(5)	0.079	3.009	0.079	3.008	0.072	2.723	0.073	2.724
α	(5)	0.110	2.135	0.109	2.134	0.118	1.917	0.118	1.917
$soilprice_s^b$	(5)	0.780	9.270	0.780	9.263	0.683	5.761	0.683	5.762
$\exp(CAPUT_{s-1})$	(5)	0.235	2.013	0.235	2.014	0.205	1.714	0.204	1.710
$LEADTIME_{s-1}/100$	(5)	0.061	2.897	0.061	2.898	0.059	2.769	0.059	2.769
$SHARE5_s$	(5)	-0.416	-4.258	-0.416	-4.257	-0.423	-4.350	-0.423	-4.349
$T1_s$	(5)	0.336	3.762	0.336	3.758	0.311	3.440	0.310	3.439
Constant	(6)	-14.050	-2.460	-14.088	-2.458	-14.052	-2.461	-14.600	-2.530
$rigrate_{s-1}$	(6)							0.114	0.603
$remres_{s-1}$	(6)	0.938	1.299	0.942	1.301	0.936	1.296	0.861	1.177
α	(6)			0.109	2.134				
$soilprice_s^b$	(6)			-0.016	-0.078				
$TCAPUT_{s-1}{}^c$	(6)	0.811	15.174	0.813	14.319	0.811	15.177	0.799	14.024
$SHARE4_s$	(6)	0.736	1.950	0.740	1.944	0.734	1.943	0.711	1.879
$depth_s$	(6)	0.894	3.456	0.902	3.281	0.896	3.463	0.870	3.320
$SEAS2_s$	(6)	0.441	2.257	0.441	2.259	0.441	2.255	0.428	2.185

Table B1. (Continued)

Variable etc.	Eq.	Models							
		Model 4		Model 5		Model 6		Model 7	
		Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.
Constant	(5)	4.173	1.894	4.843	2.911	7.210	3.212	4.858	2.704
$DUM1999_s$	(5)	0.150	1.409						
$DUM2000_s$	(5)			-0.094	-0.723				
$DUM2005_s$	(5)					0.317	1.915		
$remres_{s-1}$	(5)	0.521	2.056	0.477	2.375	0.308	1.288	0.469	2.189
RIR_{s-1}	(5)	0.084	3.263	0.078	2.961	0.064	2.433	0.078	2.997
α	(5)	0.072	1.504	0.146	1.945	0.090	1.382	0.109	2.135
$soilprice_s$[b]	(5)	0.766	7.681	0.814	8.327	0.550	3.739	0.780	9.269
exp($CAPUT_{s-1}$)	(5)	0.325	2.436	0.183	1.304	0.132	1.035	0.234	2.006
$LEADTIME_{s-1}/100$	(5)	0.062	2.983	0.058	2.704	0.048	2.216	0.061	2.898
$SHARE5_s$	(5)	-0.419	-4.346	-0.417	-4.291	-0.416	-4.339	-0.416	-4.257
$T1_s$	(5)	0.401	3.585	0.307	3.144	0.328	3.475	0.336	3.758
Constant	(6)	-16.859	-2.889	-15.333	-2.531	-13.248	-2.176	-12.956	-2.196
$DUM1999_s$	(6)	-0.332	-1.752						
$DUM2000_s$	(6)			-0.120	-0.621				
$DUM2005_s$	(6)					0.087	0.379		
$remres_{s-1}$	(6)	1.219	1.679	1.058	1.416	0.869	1.171	0.849	1.160
RIR_{s-1}	(6)							-0.042	-0.709
$TCAPUT_{s-1}$[c]	(6)	0.813	15.477	0.813	15.223	0.800	12.950	0.801	14.482
$SHARE4_s$	(6)	0.747	2.015	0.739	1.962	0.719	1.902	0.722	1.915
$depth_s$	(6)	0.991	3.792	0.944	3.509	0.863	3.147	0.864	3.306
$SEAS2_s$	(6)	0.445	2.324	0.440	2.258	0.436	2.228	0.434	2.224

Table B1. (Continued)

Variable etc.	Eq.	Models							
		Model 8		Model 9		Model 10		Model 11	
		Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.
Constant	(5)	-16.784	-1.666	4.459	2.730	6.437	1.131	3.784	0.526
$BUILD_s$	(5)	0.011	2.182						
$remres_{s-1}$	(5)	0.460	2.218	0.529	2.687				
pot_{s-1}	(5)					0.220	0.394		
$remrec_{s-1}$	(5)							0.525	0.682
RIR_{s-1}	(5)	0.079	3.105	0.084	3.235	0.078	2.856	0.076	2.772
α	(5)	0.111	2.042	0.148	2.117	0.134	2.111	0.129	2.239
$soilprice_s^b$	(5)	0.723	8.476	0.718	8.968	0.811	5.560	0.861	5.071
$\exp(CAPUT_{s-1})^c$	(5)	0.298	2.555	0.261	2.277	0.272	2.060	0.266	2.207
$LEADTIME_{s-1}/100$	(5)	0.056	2.709	0.047	2.131	0.062	2.825	0.061	2.782
$CONLENGTH_s/100$	(5)			0.031	2.059				
$SHARE5_s$	(5)	-0.381	-3.945	-0.441	-4.605	-0.457	-4.635	-0.456	-4.640
$T1_s$	(5)	0.352	4.055	0.340	4.224	0.383	3.641	0.420	3.511
Constant	(6)	-20.057	-0.487	-14.049	-2.460	-2.150	-0.264	-5.756	-0.657
$BUILD_s$	(6)	0.003	0.147						
$remres_{s-1}$	(6)	0.932	1.290	0.939	1.299				
pot_{s-1}	(6)					-0.508	-0.614		
$remrec_{s-1}$	(6)							-0.144	-0.150
$TCAPUT_{s-1}^b$	(6)	0.811	15.060	0.811	15.175	0.814	14.685	0.824	15.408
$SHARE4_s$	(6)	0.734	1.933	0.736	1.950	0.751	1.972	0.765	2.009
$depth_s$	(6)	0.868	2.513	0.894	3.454	0.938	3.649	0.960	3.721
$SEAS2_s$	(6)	0.439	2.248	0.440	2.254	0.448	2.276	0.449	2.279

[a] The data cover the period 1991q4-2013q4 except for 2008q4 and 2009q1.

[b] $soilprice_s = \log\left[\sum_{j=0}^{47} \hat{\alpha}\left(1-\hat{\alpha}\right)^j \times OILPRICE_{s-j}\right]$.

[c] $TCAPUT_s = \log(CAPUT_s) - \log(1-CAPUT_s)$.

Table B2. Estimation diagnostics

Model	R^2	DW	LM-test for hetero-skedasticity[a]
Rigrate			
Reference model	0.836	1.808	0.183
Model 1	0.836	1.808	0.183
Model 2	0.838	2.000	0.148
Model 3	0.838	2.001	0.148
Model 4	0.839	1.867	0.295
Model 5	0.837	1.804	0.165
Model 6	0.843	1.906	0.253
Model 7	0.836	1.808	0.184
Model 8	0.845	1.728	0.128
Model 9	0.843	1.794	0.239
Model 10	0.827	1.707	0.360
Model 11	0.827	1.723	0.332
log[*CAPUT/(1-CAPUT)*]			
Reference model	0.785	1.646	0.356
Model 1	0.785	1.647	0.361
Model 2	0.785	1.645	0.356
Model 3	0.786	1.638	0.292
Model 4	0.792	1.661	0.407
Model 5	0.786	1.639	0.374
Model 6	0.785	1.635	0.331
Model 7	0.786	1.630	0.355
Model 8	0.785	1.639	0.357
Model 9	0.785	1.646	0.356
Model 10	0.781	1.614	0.287
Model 11	0.781	1.618	0.321

[a] The figures reported in this column are significance probabilities. The null hypothesis is no heteroskedasticity.

Table B3. Additional variables involved for the models in Appendix B

Variable	Description	Type of underlying variable	Source	Denomination
CONLENGTH	Mean of lead times	Varies across observational unit and time	Clarksons Platou Offshore	No. of days
BUILD	Mean building year of rigs	Time invariant characteristic	Clarksons Platou Offshore	Years
pot	Log of production potential less accumulated production	Time series from the outset	Norwegian Petroleum Directorate	Million standard cubic meter o. e.
remrec	Log of remaining resources	Time series from the outset	Norwegian Petroleum Directorate	Million standard cubic meter o. e.
DUM1999	Switch from 0 to 1 in 1999	Step dummy	Norwegian Petroleum Directorate	Binary variable
DUM2000	Switch from 0 to 1 in 2000	Step dummy	Norwegian Petroleum Directorate	Binary variable
DUM2005	Switch from 0 to 1 in 2005	Step dummy	Norwegian Petroleum Directorate	Binary variable

Appendix C. Assumptions about exogenous variables employed in the different simulations

Table C1. Assumptions with respect to exogenous variables in the reference simulation[a]

Period	RIR_{s-1}	$OILPRICE_s$	$remres_{s-1}$
2014q1	1.51781	100.48929	8.07714
2014q2	1.35883	101.75970	8.08626
2014q3	0.57052	94.15097	8.09529
2014q4	0.71636	70.95670	8.08672
2015q1	1.07504	50.75970	8.07807
2015q2	2.06163	58.13927	8.06934
2015q3	2.34724	49.2	8.06054
2015q4	2.53628	47	8.06054
2016q1	2.13189	48	8.06054
2016q2	1.12110	49.5	8.06054
2016q3	1.37169	51.5	8.06054
2016q4	1.48347	52.5	8.06054

[a]For the remaining exogenous variables we employ the following assumptions:
$depth_s = depth_{2013q4}$; s=2014q1,…,2016q4,
$LEADTIME_s = LEADTIME_{2013q4;}$ s=2014q1,…,2016q4,
$SHARE4_s = SHARE4_{2013q4}$; s=2014q1,…,2016q4,
$SHARE5_s = SHARE5_{2013q4}$; s=2014q1,…,2016q4,
$T1_s$=0; s=2014q1,…,2016q4, ;
$SEAS2_s = SEAS2_{s-4}$; s=2014q1,…,2016q4.

The difference between the reference simulation and the alternative simulation *Higher oil price* is that one in the latter assumes that $OILPRICE_s$ = 100 for s=2014q1,…,2016q4 instead of the path of the oil price variable given in Table C1. The difference between the reference simulation and the simulation *Larger reserves* is that one in the latter assumes the following path for the variable $remres_{s-1}$.

Table C2. Assumptions with respect to $remres_{s-1}$ in the simulation *Larger reserves*

Period	
2014q1	8.07714
2014q2	8.08626
2014q3	8.09529
2014q4	8.08672
2015q1	8.07807
2015q2	8.06934
2015q3	8.06054
2015q4	8.09086

Table C3. Forecasts of rig rates in the reference simulation and in the two alternative simulations

Period	Reference case		*Higher oil price*		*Larger reserves*	
	RIGRATE	*CAPUT*	*RIGRATE*	*CAPUT*	*RIGRATE*	*CAPUT*
2014q1	435215.4	0.965	435027.4	0.965	435215.4	0.965
2014q2	429484.8	0.961	428657.1	0.961	429484.8	0.961
2014q3	403061.8	0.940	404444.0	0.940	403061.8	0.940
2014q4	390737.7	0.919	402222.9	0.919	390737.7	0.919
2015q1	382378.7	0.897	410679.3	0.897	382378.7	0.897
2015q2	392964.9	0.912	435888.5	0.912	392964.9	0.912
2015q3	390370.3	0.890	450253.2	0.890	390370.3	0.890
2015q4	375435.7	0.868	450145.2	0.868	380818.0	0.870
2016q1	348135.2	0.850	432260.7	0.850	358514.4	0.858
2016q2	309033.8	0.880	395645.5	0.880	323403.8	0.893
2016q3	312935.7	0.861	411366.4	0.861	332568.9	0.882
2016q4	306971.9	0.846	412649.8	0.846	331813.3	0.878

Table C4. 50% forecast interval for rig rates and capacity utilization in the reference simulation

Period	Rig rate	Capacity utilization
2014q1	[376993.4; 499413.7]	[0.955; 0.981]
2014q2	[369028.2; 487085.9]	[0.951; 0.986]
2014q3	[346208.8; 457639.5]	[0.924; 0.982]
2014q4	[334768.8; 442637.3]	[0.894; 0.977]
2015q1	[325558.3; 433966.6]	[0.864; 0.972]
2015q2	[334817.2; 445882.5]	[0.887; 0.978]
2015q3	[331785.6; 440077.0]	[0.855; 0.971]
2015q4	[323728.2; 429859.4]	[0.825; 0.966]
2016q1	[304068.9; 403537.3]	[0.807; 0.961]
2016q2	[271566.8; 365683.7]	[0.859; 0.973]
2016q3	[281492.9; 377076.4]	[0.841; 0.969]
2016q4	[281781.0.; 373020.4]	[0.836; 0.968]

Appendix D. Forecasting and forecasting uncertainty

Let:

(8) $y_s = rigrate_s, \quad x_s = CAPUT_s$,

Our model may then be specified as:

(9)

$$y_s = \delta_1 \exp\left(x_{s-1}\right) + g\left(Z_s, \lambda_1\right) + \varepsilon_{ys}, \quad \log\left(\frac{x_s}{1-x_s}\right) = \delta_2 \log\left(\frac{x_{s-1}}{1-x_{s-1}}\right) + h\left(M_s, \lambda_2\right) + \varepsilon_{xs}$$

where $g\left(Z_s, \lambda_1\right)$ and $h\left(M_s, \lambda_2\right)$ are terms that capture the effects of the exogenous variables. Let ^ denote a multiple regression estimate. Then residuals may be calculated as:

(10)

$$\hat{\varepsilon}_{ys} = y_s - \left[\hat{\delta}_1 \exp\left(x_{s-1}\right) + g\left(Z_s, \hat{\lambda}_1\right)\right], \quad \hat{\varepsilon}_{xs} = \log\left(\frac{x_s}{1-x_s}\right) - \left[\hat{\delta}_2 \log\left(\frac{x_{s-1}}{1-x_{s-1}}\right) + h\left(M_s, \hat{\lambda}_2\right)\right]$$

Let *S* denote the number of observations in the estimation period. The $Sx2$ matrix with residuals is given by:

(11)
$$\hat{\varepsilon}_{yx} = \begin{bmatrix} \hat{\varepsilon}_{y1991q4} & \hat{\varepsilon}_{x1991q4} \\ \vdots & \vdots \\ \hat{\varepsilon}_{y2008q3} & \hat{\varepsilon}_{x2008q3} \\ \hat{\varepsilon}_{y2009q2} & \hat{\varepsilon}_{x2009q2} \\ \vdots & \vdots \\ \hat{\varepsilon}_{y2013q4} & \hat{\varepsilon}_{x2013q4} \end{bmatrix}$$

Consider (10) for the first 12 quarters after the last observation in the estimation sample. Then the following 24 error terms are involved:

(12)
$$\varepsilon_{yx}^F = \begin{bmatrix} \varepsilon_{y2014q1} & \varepsilon_{y2014q2} & \cdots & \varepsilon_{y2016q4} \\ \varepsilon_{x2014q1} & \varepsilon_{x2014q2} & \cdots & \varepsilon_{x2016q4} \end{bmatrix}$$

To account for forecasting uncertainty we generate 6000 replications utilizing the empirical distribution of the within-sample residuals. The different rows in ε_{yx}^{F} are drawn independently. We retain the correlation of the two error terms that is from the same period by drawing rows from the $\hat{\varepsilon}_{yx}$ matrix. In an arbitrary replication each row in $\hat{\varepsilon}_{yx}$ has an equal probability of 1/*S* to be picked out. We then solve the following equations recursively for *s* = 2014q1-2016q4.

(13)

$$\hat{y}_s^{\{j\}} = \hat{\delta}_1 \exp\left(\hat{x}_{s-1}^{\{j\}}\right) + g\left(Z_s, \hat{\lambda}_1\right) + \varepsilon_{ys}^{\{j\}}, \quad \hat{x}_s^{\{j\}} = \frac{\exp\left(\hat{\delta}_2 \log\left(\dfrac{\hat{x}_{s-1}^{\{j\}}}{1-\hat{x}_{s-1}^{\{j\}}}\right) + h\left(M_s, \hat{\lambda}_2\right) + \varepsilon_{xs}^{\{j\}}\right)}{1+\exp\left(\hat{\delta}_2 \log\left(\dfrac{\hat{x}_{s-1}^{\{j\}}}{1-\hat{x}_{s-1}^{\{j\}}}\right) + h\left(M_s, \hat{\lambda}_2\right) + \varepsilon_{xs}^{\{j\}}\right)},$$

where the superscript *j* denotes the replication number. Note that (for all *j*) we have $y_{2013q4}^{\{j\}} \equiv y_{2013q4}$, $x_{2013q3}^{\{j\}} \equiv x_{2013q3}$ and $x_{2013q4}^{\{j\}} \equiv x_{2013q4}$. Let $Y_s^{\{j\}} = \exp\left(y_s^{\{j\}}\right)$. In the *j*th replication we thus obtain the following forecasts:

(14) $$G_{yx}^{F\{j\}} = \begin{bmatrix} Y_{2014q1}^{\{j\}} & Y_{2014q2}^{\{j\}} & \cdots & Y_{2016q4}^{\{j\}} \\ x_{2014q1}^{\{j\}} & x_{2014q2}^{\{j\}} & \cdots & x_{2016q4}^{\{j\}} \end{bmatrix}$$

In the first column of $G_{yx}^{F\{j\}}$ we have the forecasts of the mean rig rate and in the second column the forecasts of the capacity utilization rate. Let generally the number of replications be denoted by *J*. As point forecasts we now have:

(15) $$\breve{Y}_s = \frac{1}{J}\sum_{j=1}^{J} Y_s^{\{j\}}, \quad \breve{x}_s = \frac{1}{J}\sum_{j=1}^{J} x_s^{\{j\}},$$

Let $f_{0.25}^{Y,s}$ and $f_{0.75}^{Y,s}$ denote, respectively, the first and third quartile in the distribution of replicated rig rates in period s, and let, correspondingly, $f_{0.25}^{x,s}$ and $f_{0.75}^{x,s}$ denote the first and third quartile in the distribution of replicated capacity utilization rates in the same period. The 50% bootstrapped forecast intervals in period *s* are then given by:

(16) $$\left[f_{0.25}^{Y,s}, f_{0.75}^{Y,s} \right] \text{and} \left[f_{0.25}^{x,s}, f_{0.75}^{x,s} \right]$$

with $s = 2014q1,...,2016\,\mathrm{q}\,4$.

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