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From Sea to Shining Sea?

An econometric inquiry into the offshore mobile rig market

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Abstract

The mobile offshore development unit (MODU) market is unique in that the majority of the rig fleet is owned by independent rig management firms and leased to oil and gas companies for exploration and production. Managing a firm's fleet is a complex profit maximization process by which managers decide what rigs to keep active in search of contracts, temporarily idle or cold stack, reactivate from cold stacking, upgrade, or sell. Despite the substantial financial implications of these decisions, empirical research on the MODU market has been limited. We therefore take advantage of a substantially larger dataset and utilize existing models as a starting point to describe both the idling and rig day rates for active rigs. For idling behavior, the decision to cold stack is presented using a real option framework. The contract day rate model is described using a multiple linear regression. The purpose of this paper is to re-examine existing models and to suggest additional factors driving both idling behavior and rig day rates. In general, these decisions are seen as being driven by a rigs utility via observable and unobservable heterogeneity, market conditions, as well as a firms' size. In particular, lagged factor prices and rig utility proxies such as rig moves across geographic regions are the best determinants of rig idling options while most rig characteristics are otherwise mixed. After controlling for regional and time effects, the main determinants of day rates are utilization rates and rig moves across regions. Factor prices, on the other hand, have no significant effect on rig rates. Through a better understanding of idling and contract day rate dynamics, our research is relevant to rig owning and operating firms as well as the financial institutions that support them.

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Contents

1. Introduction

The need for offshore oil and gas has always been driven by a combination of dwindling onshore production and relatively high factor prices. These high prices have justified the capital investments to survey, explore, and potentially produce a given offshore field (Kaiser and Snyder, 2013a). While stylized, this vignette is demonstrative of both the economic challenges faced by offshore market participants and the driving forces behind more ambitious – deeper and farther offshore – projects over time.

Despite the recent shifts in the global energy mix – particularly from unconventional, and predominantly onshore, sources – oil remains and is expected to remain the leading primary energy source through 2035 (IEA, 2013). Of the approximately 90 million barrels of oil produced daily around the world, 30 million barrels per day (mbpd) are produced offshore and 13 mbpd are produced on a mobile offshore development unit (MODU): a generic distinction given to the collective group of jackups, semisubmersibles (semisubs), and drillships (BP, 2013; Kaiser and Snyder, 2013a). The offshore market's share of total oil and gas production is also expected to remain at this same level well into the next decade, sustained primarily from an increase in production from MODUs (Infield Systems, 2012).

Unlike their fixed offshore peers, MODUs are capable of working farther from shore and in multiple locations over the course of their operational life. Furthermore, third party rig owners, rather than oil and gas companies (O&G), own the majority of the MODU fleet. Rig owners provide a sound partner for an oil and gas company to mitigate the risk of operating in the offshore environment. While rig owners will not typically build a new rig without a contract for exploration or production work in hand (Corts and Singh, 2004), this has never encouraged O&G to be more than a minor player in the MODU fleet: of the more than 1,400 MODUs currently operating, less than five percent are wholly owned by O&G (RigLogix, 2014).

Contracts for a newly built rig can vary in length from a few weeks to many years, after which a rig either extends its contract via an embedded contract option or can make a number of decisions with respect to its operational status. First, and what is the most frequent decision, a rig can re-enter the (spot) market in search of new contracts or tenders. If an active rig is not currently under contract, this is known as a ready stacked rig. Occasionally a rig will move regions as part of its contract conditions. The costs associated with moving a rig, regional rig specifications, and local regulations are legitimate reasons to consider the MODU market within a regional framework (Kaiser and Snyder, 2013b; Osmundsen et al., 2008). While still relatively rare, rig movements have almost doubled as a share of total contracts from 2004 to 2013 (from almost 6% to 12%) and thus are worth investigating closer. Second, a rig can temporarily idle itself in a process known as cold stacking. A cold stacked rig is stored in safe location – harbor or shallow bay – and cannot re-enter the market without incurring substantial financial costs (anywhere between 10-30 million USD), time (one to two months), and potential specialist labor shortages (Kaiser and Snyder, 2013a). Third, a rig can undergo modifications or upgrades in order to become more competitive relative to newer rigs. Modifications also occur as part of a contract with a company that guarantees said rig work after the completion of modifications. Finally, a rig can be sold to a competitor or for scrap.

Despite these trends in offshore oil markets, relatively little empirical work has been written on rig owner’s decision making in the MODU market. The existing literature has focused largely on rig managers or oil producers (for example, see Mauritzen, 2014; Kellog, 2010; Osmundsen et al., 2009; Mohn and Osmundsen, 2008; Hamilton, 2008; Lee and Ni, 2002). In light of the large capital costs or the specialized labor associated with operating a rig, our understanding of the effects of both market forces and rig heterogeneity on both real option values of keeping a rig active versus cold stacked and contract day rates earned by rig owners deserves to be developed further. An empirical analysis of the relevant factors effecting day rates or option values would be a gain to both the operational divisions of rig owning or operating firms – identifying what factors drive both their own and their competitors’ decision making – as well as the institutions and investors responsible for financing said firms. Their benefits would come from a more sound understanding of MODU market dynamics.

Utilizing a global MODU data series, the aim of our research is to examine and replicate existing cold stacking real option and contract rate formation models, originally presented by Corts (2008) and Osmundsen et al. (2012) respectively. Both models claim that higher specification rigs can command a higher contract rate and are also less likely to be cold stacked due to their high utility. After controlling for firm size, rig type, region and time period, Corts proved that this likelihood of cold stacking a rig is positively related to the age and negatively related to the rig water depth and the deck load of the rig. He also found that larger firms are more likely to stack and reactivate rigs at a higher frequency than smaller firms. Corts concluded this was due to a larger firms' ability to retain labor. Osmundsen et al. (2012) showed that offshore rig day rates are positively related to the utilization rates, factor prices – gas prices in particular– and are significantly effected by contract characteristics, such as contract length and lead time.

These models and their hypotheses form the basis of our research questions. While testing the reproducibility of published research has in itself become a growing component of published empirical work (Economist, 2014), the additional contributions of our thesis to the existing literature are fourfold. First, it is our inclusion of factor prices, all available rig types, and all available global regions to our model specifications. Second, is our treatment and inclusion of latent variables, such as rig moves, to better understand the effect unobservable heterogeneity has on cold stacking and contract day rates. Thirdly, rather than frame the cold stacking decision as a binary decision – active versus cold stacked – we include a multinomial logistic model. While the real option value of a rig is not disputed – serving as a floor on the operational losses incurred by a firm – a multinomial model allows us to determine the effect of rig heterogeneity on the idling as well as all other aforementioned decisions available to rig owners. Finally, we include additional explanatory variables in order to more properly specify our day rate model.

Given our extensive dataset, we take the opportunity to examine some of the market trends we observe from our series, combined with a general overview of the MODU market, and the relevant descriptive statistics used in our models. This is presented in section 2. Otherwise, the remainder of this paper is structured as follows. Section 3 presents the literature review. Section 4 introduces the data used in our analysis. Section 5 lays out the theoretical framework for our models. Section 6 presents our empirical results, and section 7 offers our concluding remarks and avenues for future research.

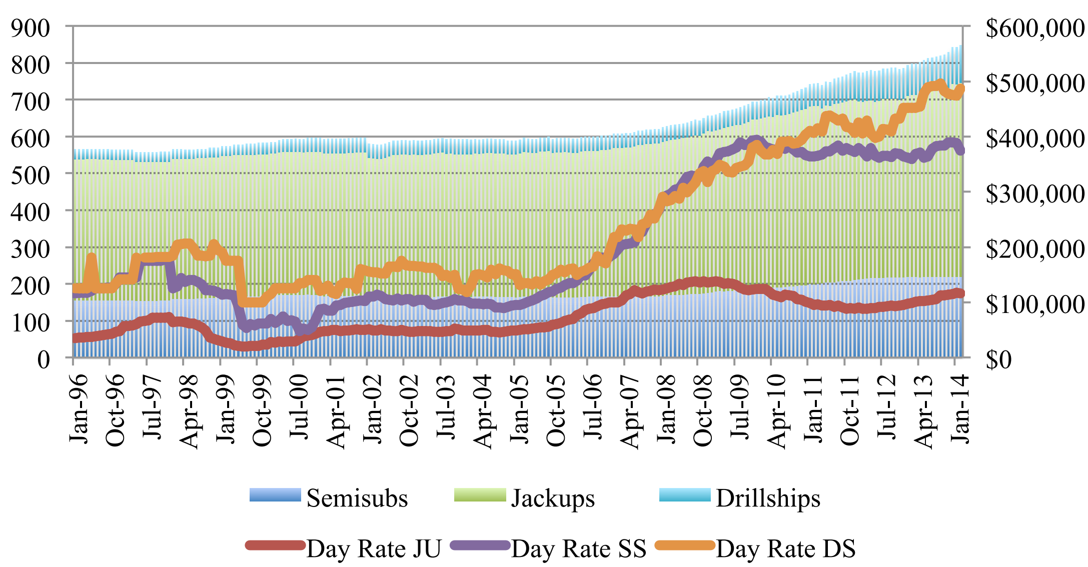
2. The MODU market: A brief overview

As presented in the introduction, the MODU market is composed of three primary rig types: jackups, semisubs and drillships. Secondary rig types are both few in number and rarely operate in the same environments as primary rigs – shallow, inland, and small discoveries versus deep, offshore, and large discoveries (Schempf, 2007). For this reason all secondary rigs – rigs unfit for ocean usage – will be excluded from our analysis. The terms rig and MODU will be used interchangeably in the remainder of this paper.

Jackups, largely due to design specifications, – a series of cantilevered legs that must be affixed to the ocean floor or a man-made sea bed pad – operate in water no deeper than 600 feet (RigLogix, 2014). Semisubs and drillships are capable of drilling in significantly deeper water by maintaining their location at a drill site via dynamic positions (DP) or mooring lines (Noble, 2013). Existing semisubs have a maximum water depth of 12,000 feet and drillships are presently capable of operating in water as deep as 27,000 feet (RigLogix, 2014).

The higher specifications required of semisubs and drillships compared to jackups translate into both higher operating costs and higher average contract day rates for rig owners [see figure 1]. In a competitive market, the day rates charged are the best available proxy for the costs incurred by the operators (Corts, 2008). Rarely do the day rates of drillships or semisubs equal or drop below those of jackups. However, this has occurred in 1997 and late 2000 for drillships and semisubs respectively. This highlights a crucial dynamic: in poor market conditions both drillships and semisubs can be contracted out for work by O&G to do the work normally carried out by jackups. The opposite however, is technically not feasible.

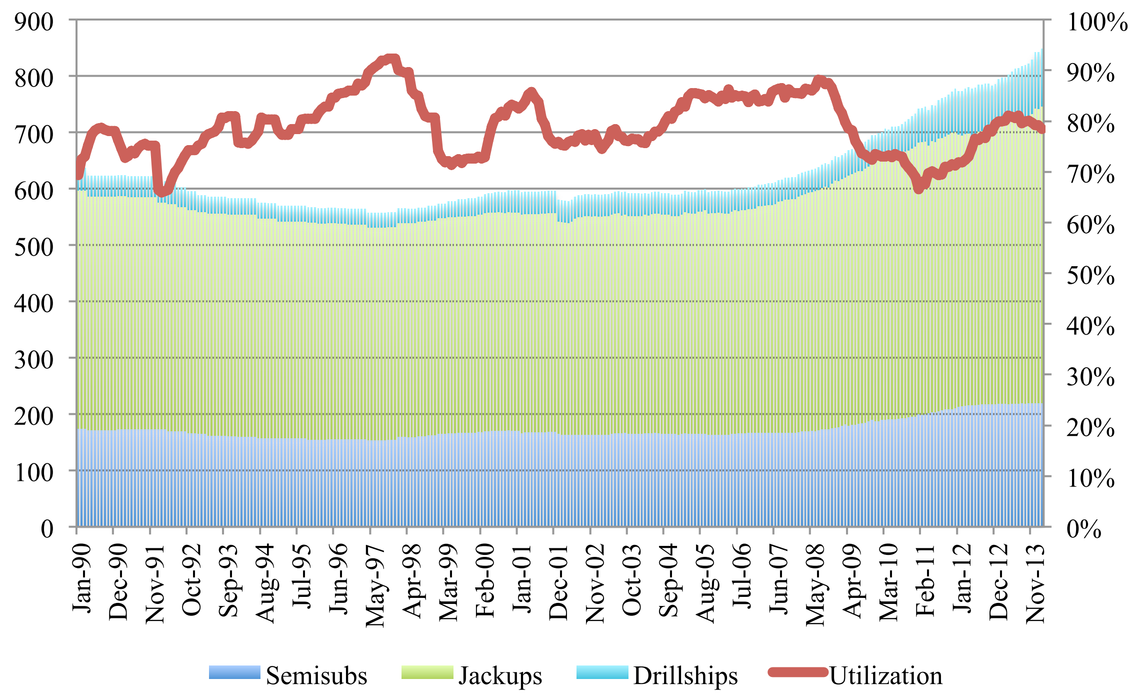
Figure 1: MODU Count and Day Rates 1996-2014



Source: RigLogix, 2014.

The operational advantages of drillships and semisubs notwithstanding, the majority of the MODU market is made up of jackups [see figure 2]. From 1990-2014[1], the number of active (non-cold stacked) jackups have made up an average of 66% of the MODU market. This figure has dropped from that average since 2008 and is presently around 62%, due to a relatively large number of drillships and semisubs entering the market. Net additions to the drillship and semisub market have risen by 60 and 50 rigs respectively since 1990. These values reaffirm the often cited trend of offshore O&G projects moving further offshore and thus requiring the kinds of rigs capable of operating in these more challenging environments (RS Platou, 2014; The Economist, 2010).

Figure 2: Active MODU Count and Utilization 1990-2014



Source: RigLogix, 2014

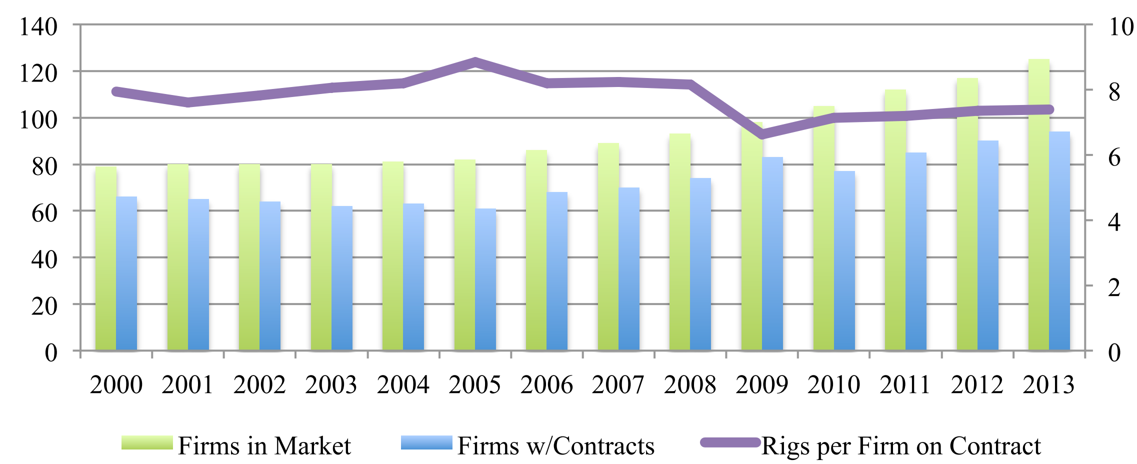
The number of rigs active at any given moment is only one method of surveying the strength or weakness of the MODU market. The utilization rate – the ratio of rigs currently under

[1]Time series varied across variables in order to take advantage of all data made available to the researchers. Note this was only the case for this section, as our models all utilize the same series length in an effort of continuity.

contract relative to total number of active rigs in the market[2] – provides a sounder metric of the amount of excess market capacity on any given month [see figure 2]. Macroeconomic shocks including the recessions of 2001 and 2008 were correlated with drops in utilization rates (Kaiser and Snyder, 2013a). Decreases in utilization rates are only exacerbated by the aforementioned shifts in MODU supply, most notably during the last five years.

Decreasing utilization rates and an increase in the rig count is symptomatic of another MODU market trend – that of increased market participation. Despite larger firms such as Transocean Ltd. and Noble Drilling Corp. owning almost half of all rigs on contract (RigLogix, 2014), the number of firms operating in the MODU market has risen from 79 in 2000 to 125 in 2013 [see figure 3]. While the average number of rigs per firm on contract appears stable, larger market participants easily skew this figure. However, the number of firms with at least one rig on contract during a given year has followed this upward trend. This is indicative that even small rig owning firms are able to secure business. Concentrated market share does not mean limited participation for new entrants. Similar to large O&G, large firms often sell off less profitable rig market segments to smaller firms specializing in said segment or to newer firms looking to gain market entry via the secondhand market (RS Platou, 2014).

Figure 3: Rig Count 2000-2013



Source: RigLogix, 2014

[2] Active would include all rigs that are ready stacked or on contract, but not those cold-stacked or undergoing modification.

While more firms can create healthy competition in the MODU market, our hypotheses about firm size focus instead on large firms' ability to take advantage of economies of scale. First, are larger firms able to operate at lower contract rates due to lower operating costs per rig? Second, are larger firms more willing to cold stack or reactivate a rig due to their ability to more easily retain the specialized labor needed to staff a rig? Both questions are formally presented in our theoretical framework section as a component of the real option and contract day rate models.

2.1 Labor and capital costs

The costs associated with the exploration and production of oil has increased substantially over time. The costs per well drilled in US (both onshore and offshore), when adjusted for inflation, have grown from $470,000 in 1990 to almost $3,500,000 in 2007 (EIA, 2014). The largest components (around two thirds of all associated costs) are the day rates paid to the operator of the rig and the costs of oil services (Osmundsen et al., 2009).

The cost structure in the offshore rig industry can be well approximated by two parts – operating expenses (also known as contract drilling services expenses) and depreciation and amortization. While the companies that own and operate a rig fleet incur other expenses as well (impairment of assets, administrative, financial, etc.), those are of minor magnitude.

The daily operating expenses vary between the companies. For example, according to information provided by Seadrill (2013) these costs amount to $170,000 per rig, while in case of Ocean Rig (2012) the daily operating expenses are estimated to be $235,000 per rig. The level of operating expenses (relative to cash inflows and reactivation costs) has a pronounced influence on the idling decisions (Corts, 2008). Operating expenses include the labor costs (onshore and offshore crew) and costs incurred when maintaining the rig to its appropriate operational standards while on contract. Labor costs are both significant and sticky. They can amount up to 42% of the operational expenses (Transocean, 2013). However, the companies cannot quickly adjust their demand for labor according to the market conditions, as it takes time and financial resources to fire and hire employees. Therefore, labor hoarding is a prevalent practice that partially explains the incidence of excess capacity in the oil and gas drilling industry (Ishii, 2010). Larger companies (as measured by the number of rigs in the fleet) can offset the negative impact of labor costs by assigning the crew from deactivated rigs to active ones (Corts, 2008). Thus the larger the company is, the more flexibility it has when making idling decisions with respect to labor (and thus operational) costs.

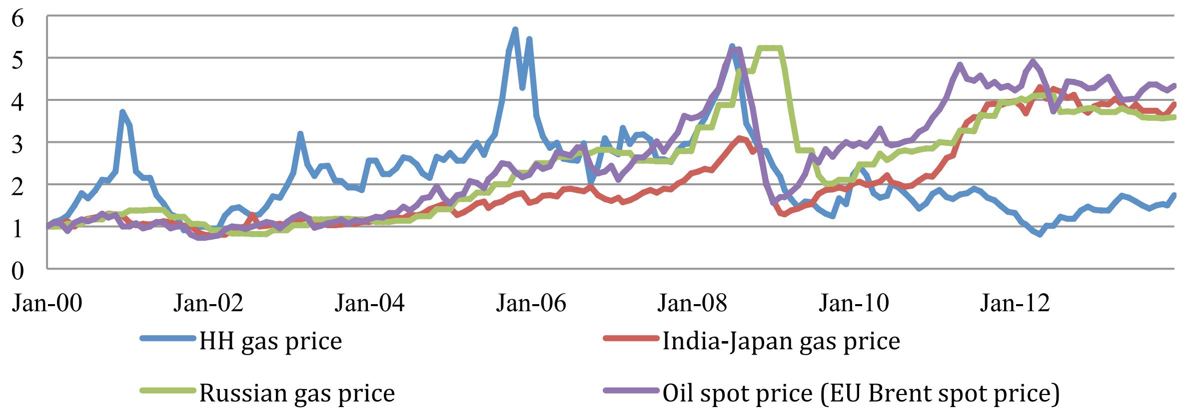
Depreciation and amortization costs, on the other hand, reflect the sunk costs incurred when ordering a rig in the newbuild market or when acquiring one in the secondhand market. Those investments are capitalized over the operational lifetime of the rig (usually set to be 30 years for new rigs, Seadrill, 2013). The offshore rig market is capital intensive, as the average construction costs of newbuild rigs that were delivered in the period 2000-2013 ranged from $110,000,000 to almost $500,000,000 (RigLogix, 2014).

Rig construction costs are determined by market-wide dynamics, shipyard heterogeneity, and the rig's specifications (Kaiser and Snyder, 2012). The class of the rig and its features determine the material, labor costs and needs for equipment. The drillships are, on average, the most expensive to build, followed by semisubs and jackups. Therefore, we would expect this to be reflected in the day rates and thus the day rates earned by drillships should be significantly higher than by other categories of rigs.

2.2 Macroeconomic environment

Between January 2000 and December 2013, the development of the factor prices could be characterized by substantial variations compared to that of utilization rates [see figure 4]. The oil price and gas prices followed each other relatively closely until 2008. Afterwards, the series decoupled largely thanks to the regionalized nature of the gas markets, increasing supplies of shale gas, and increased political turmoil in the Middle East.

Figure 4: Development of deflated Factor Prices (base period January, 2000)



Source: Macrobond, 2014

The changes in utilization rates, on the other hand, showed much lower variation. As described above, the incidence of excess capacity in the market does not discourage market participants to discontinue their operations due to the option value of keeping a rig active.

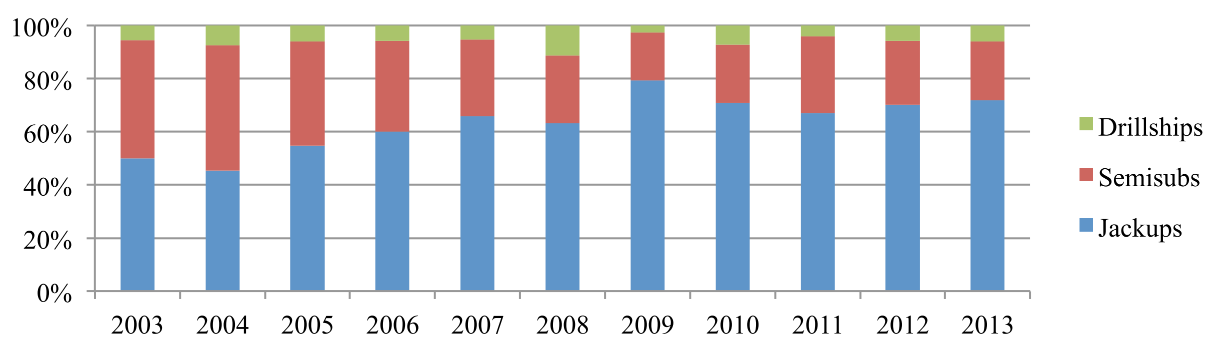
The relationship between the one-period lagged utilization rates and the deflated factor prices seem to be inverse – pairwise comparison reveal that correlation during the period of analysis between the oil price and one-period lagged utilization rate is -0.09, while the relationship between the gas prices and utilization rates is 0.61, -0.17 and 0.15 for Henry-Hub, India-Japan and Russian series of the gas prices respectively. A higher correlation coefficient with respect to Henry-Hub gas prices might be a result of the sample that is skewed towards rigs operating in the Gulf of Mexico. Therefore, in accordance with the results presented by Osmundsen et al. (2012), who used deflated factor prices in their analysis, we would expect that gas prices have more pronounced positive impact when explaining the formation of the day rates, if the factor prices affect the day rates through utilization rates mainly. However, the correlation coefficient between the real oil prices and deflated day rates is positive and substantial (0.46), thus oil prices should matter when explaining day rates.

2.3 Rig types

Consistent with the popularity of the jackups identified above, 66% of the contracts (almost 9,000) between January 2000 and December 2013 were written for this type of the rig. Contracts for drillships and semisubs constituted 5% and 29% of the sample respectively. The day rates charged for different types of rigs reflected well higher construction costs and more diverse operating capabilities of the drillships. The average nominal day rate for the drillships was around $316,000, while for jackups and semisubs the day rates were, on average, around $76,000 and $204,000 respectively.

When analyzing the distribution of rig types over time [see figure 5], the jackups were the most popular choice throughout the period, while the share of drillships peaked in year 2008 to 11% of the contracts. Increased share of drillships is consistent with increased need to extract oil in more hostile environments and thus higher demand for rigs able to withstand them.

Figure 5: Rig Type Distribution 2003-2013[3]



Source: RigLogix, 2014

2.4 Rig mobility

Previous researchers claim that movements across regions are rare and thus rig market is of local nature (Ringlund et al., 2008). However, our dataset speaks in favour of movements taking place – both across the countries and regions [see figure 6]. As expected, drillships are the

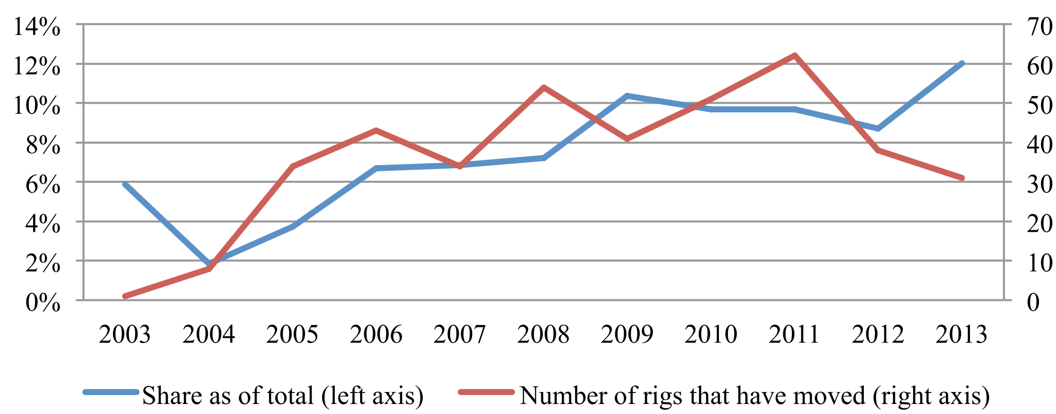
[3]Excluding period from 2000 to 2002 due to limited data availability for all rig types.

most mobile units (measured as the number of contracts that were signed for operations in an alternative country/region than the rigs current country/region). The share of contracts that were signed for drillships that required international movement is 28% over the sample period (while inter-regional movements represent 15% of the sample). For semisubs and jackups the corresponding figures are 15% (6%) and 11% (4%).

If we take a look at the day rates conditional on the rigs' movements, the rigs that have moved across the countries charge around $190,000 in nominal terms (while those that obtain a contract in the same country as the previous one charge almost $120,000). The rigs that have moved across regions earn on average $218,000 (compared to $122,000 earned by less mobile units).

We split the rigs into two categories – rigs that have moved across regions and rigs that did not – and run a two-sided t-test. The test indicates that there is a statistically significant difference between the means of the day rates (0.1% significance level). This difference combined with an increase in frequency of rig movements motivate us to investigate this issue closer and account for the movement of the rigs in both models.

Figure 6: Share and Number of Rigs that Moved across Regions 2003-2013[4]



Source: created by authors based on data from RigLogix, 2014

[4]Excluding period from 2000 to 2002 due to limited data availability and thus skewed proportionality.

3. Literature review

The empirical evidence on the factors that influence the rig owners' decision to cold stack or ready stack a rig and the formation of the rig day rates is relatively scant. Data series availability has been one constraint (Osmundsen et al., 2012). Fortunately, as the offshore industry grows, the requisite data series have simultaneously improved both for current and historic rig activity (RigLogix, 2014).

3.1 Idling decisions as real options

Real option theory dates back to the seminal work by Myers (1977) who suggested that investment decisions could be viewed as a call option on an underlying real asset. Since then, real options have been a growing component of financial economics across a wide range of market and investment decision applications [for an overview of these applications, see Dias (1999)]. Commodities leant themselves particularly well to real option models given that data was more readily available than in other markets. Oil was one of the first commodities to be studied in a real option framework by Taurinho (1979). Paddock et al. (1988) created one of the earliest analogies to the Black-Scholes option pricing models for offshore petroleum leases. Subsequent literature has debated the model specification for the parameters – the current value of the developed reserve, investment costs to develop the reserve, the volatility of the developed reserve, and so on – of Paddock et al. model or a similar variation. All sought to best identify the size and scale of options to various investment decisions inside the oil and gas sector. For instance, Fleten et al. (2010) chooses a Least Squares Monte Carlo algorithm to model oil prices and convenience yields – price paths used to determine both the current value and volatility of the reserve – while others prefer a Brownian motion stochastic model (see Ruiz-Aliseda and Wu, 2012; Ringlund et al., 2008; Dixit, 1989). While the details of this debate are beyond the scope of our research, a sound summary can be found by reading Dias (2004).

Idling behavior has been studied as early as 1968, with Mossin's seminal work on optimal lay-up strategies for shipping firms under uncertainty. However, real option values associated with entering or exiting a given market were not examined until Brennan and Schwarz (1985) included a real option variable to their natural resource investment models. However, their efforts shared the same parameter decisions, and subsequent complications, as the Paddock et al. model. Additionally, the Brennan and Schwarz model only addresses the binary decision to enter or leave a market permanently. Roberts and Tybout (1995) addressed both of these issues. First, they included parameters that allow for a temporary idling of capacity, mainly via a reactivation cost parameter. Second, they suggested proxy variables that could be used to implicitly determine whether or not real options are exercised. This arises in research, including our own, where firm heterogeneity is of a greater interest than an estimate of a given real option's value.

In more opaque and data scarce markets, the Roberts and Tybout model has provided a working solution to distinguish between characteristics that would increase (or decrease) the probability that an asset owner would exercise their option to temporarily (or permanently) exit or enter (or re-enter) a given market. If capital investments and sunk costs are large enough, an understanding of the heterogeneous characteristics associated with an option being exercised can add to the quantitative understanding of market participation. Up until now, this has proven particularly beneficial to firm and industry export behavior (Impullitti et al., 2013) as well as firm participation in carbon emission trading schemes (Zaklan, 2012). To our knowledge, the only inquiry into idling behavior in resource markets has been by Moel and Tufano (2002), who investigate the temporary closure of mines, and Corts (2008) who examines, as we do, the idling decisions of MODU owners. Temporary closures of assets have received little attention elsewhere. When measuring the probability that the rig is stacked or remains stacked Corts relied on a paneled logit model and the firm and rig characteristics as explanatory variables. Further model details will be fully developed in section 5.

3.2 Evidence on rig rate formation

When evaluating the empirical research of rig markets, the question that has garnered most of the attention is the determinants of rig activity (proxied by a number of active rigs or utilization rates). Numerous studies have addressed this starting with the one by Renshaw (1989), who investigated the effect of the changes in the oil prices on the number of rotary drilling rigs in the US. Cheng (1998) took a step further and put forth an objective to determine whether the changes in the oil prices Granger-cause changes in the drilling activity in the US (both onshore and offshore). He found empirical support for such relationship in the long run, but not in the short run. Ten years later Ringlund et al. (2008) has quantified the relationship between the crude oil price and rig activity (both onshore and offshore) in a number of non-OPEC regions via dynamic regression models. The relationship was found to be positive across the regions (with the long-run price elasticity of around one), but the magnitude of the effect of the oil price on the rig activity differed substantially. This difference was attributed to the heterogeneity in the structure of the industry.

The only authors, to our knowledge, that attempted to quantify the determinants of the offshore rig rates are Kaiser and Snyder (2013a) and Osmundsen et al. (2012). The latter authors investigated the jackup rigs in the Gulf of Mexico during the period from 1990 to 2009 and raised a hypothesis that utilization rates as well as real gas and oil prices have positive effect on the real rig rates. After controlling for rig and contract heterogeneity and utilizing a non-linear random effects model the authors have found this to be the case. This study also addressed the hypothesis that utilization rates have a non-linear effect on the rig rates – the effect of utilization rates on the rig rates increases dramatically as soon as the threshold for high utilization (set to be 98%) is crossed. In addition to this, changes in the gas prices seem to have a higher effect on the rig rates than the variations in the oil prices. Finally, the authors argued the factor prices have indirect effect on the rig rates through utilization rate.

Kaiser and Snyder (2013a) acknowledged that utilization rates is an important proxy for the level of the excess capacity in the market and thus is fundamental in forming expectations about the future day rates. However, when studying the contracts across five regions over a 10-year time period they found that utilization rates is a weak predictor of day rates, especially in the regions where the variations in the utilization levels are low (ex. in the North Sea). While Osmundsen et al. (2012) emphasized the importance of the gas prices, Kaiser and Snyder (2013) relied on oil prices only and argued for the importance of its role when determining the rig rates. In addition to macro level determinants, the authors also utilized the features of hedonic model (introduced by Rosen (1974) and used to investigate the pricing of heterogeneous good). The authors controlled for the rig (type, drilling and water depth as well as station keeping), region and contract heterogeneity and found those variables to be significant. Interestingly, after controlling for the type of the counterparty in the agreement (public versus national oil companies, NOCs), NOCs were proved to be paying higher day rates compared to public ones.

Taking a broader perspective, the issue of rig rates formation is conceptually the same as dry bulk shipping rates. Both topics share similar characteristics and thus are attributed to the common field of maritime economics. The formation of the dry bulk shipping rates has been widely addressed (see, for example, the studies by Thanopoulou and Gardner, 2012; Laulajainen, 2007; Beenstock and Vergottis, 1993). Vessels (assets that require considerable irrevocable investments) are chartered under the contracts that define the rate, the period of hire and other details. The rate can be expressed as the day rate, while the laycan period is fundamentally the same as the lead period in the rig lease market.

A recent study by Alizadeh and Talley (2011) established that vessel heterogeneity and laycan period are important determinants of the freight rates and there exist significant differences across routes. In addition to this, the authors found evidence that the freight rates and laycan periods are determined simultaneously. Variables that influence the freight rates could be clustered into macroeconomic, vessel, and contract specific factors. All of the clusters matter in the freight rate formation and thus should be accounted for (Köhn and Thanopoulou, 2011). Thus when explaining the drivers behind the rig rates, we form and investigate similar clusters.

4. Data

The data used in both our real option and day rate model come from the American data provider Rigzone and their subscription database RigLogix[5]. Specializing in the collection of offshore rig activity data via both public and private sources makes RigLogix one of the most expansive offshore databases available. Our data for both models covers 163 months of global rig activity from June 2000 to December 2013: a series that captures periods of significant volatility of both rig activity and day rates (see section 2). Better powered evidence via a larger sample size or longer series is generally beneficial towards removing bias from coefficient and standard error estimates (Wooldridge, 2012; Ioannidis, 2005). If a model was properly specified, estimates would nonetheless become more efficient, an inference confirmed by smaller standard errors.

While the RigLogix contains a comprehensive database of rig specifications as well as contract day rate information, our statistics of interest start with those included in the original

[5] http://riglogix.rigzone.com/

authors' work. Additional variables and specifications for each model are described below and in section 5 respectively.

One potential source of bias in MODU market data is the scale of offmarket or undisclosed MODU market activity. Our data provider takes every effort to provide as holistic dataset as possible: offmarket activity never represents more than one percent of total market activity in the data series (W. DiBenedetto, personal communication, May 28, 2014).

4.1 Real option model data characteristics

The summary statistics for the real option model variables can be found in table 1. Variables were chosen according to their ability to serve as proxies for rig costs and option values: a concept more fully developed in the following section (and section 5). Due to the volatility seen in the rig market over our time series, our panel data of monthly observations is unbalanced.

Given our interest in cold stacking behavior, the dependent variable in our model, *cold stacked*, is an indicator variable equaling one if the rig is active in a given month and zero otherwise. While rigs can realistically take on a number of statuses – drilling, exploration, waiting on location, workovers, etc. – we will initially focus solely on cold stacking in order to replicate Corts' preferred model specification. This means unless a rig is scrapped (or not yet built), there will be no missing observations for a given rig during our series. *Already stacked* is similarly an indicator variable equaling one if the rig was stacked in the previous month and zero otherwise. For rig specifications and independent variables we begin by mimicking Corts' model as accurately as possible[6]. We create dummy variables for the three major MODU rig types, and also include age, deep water depth, shallow water depth, and firm size in our model. Age is a discrete random variable equaling the age of the rig in years. Shallow and deep water depth are the maximum depths in feet a rig can operate (drill) at, but have been interacted with a deep/shallow dummy due to spatial differences in rigs' operational capacity in shallow versus deep water. We define *deep* as anything above 600 feet and *shallow* as anything less than or equal 600 feet. Due to the interaction dummy, the category a rig doesn't fall into will merely take a

[6] Corts' model includes deck load for each rig. This information was missing for almost half our sample size making it unsuitable for missing value imputation (see Schafer and Graham, 2002).

value of zero. Therefore, a jackup whose operational depth was 300 feet would have a shallow water depth variable equal to 300 and a deep water depth variable of zero. Firm size is another discrete variable that measures the number of rigs per firm per region per month. This definition is broadened in our model specifications, and the specifics of this decision are examined in subsection 5.1.

Regions have been divided using dummy variables and account for the existing MODU markets as defined by Kaiser and Snyder (2012). However, there were numerous geographic regions where market activity was small or limited (i.e. Alaska, Greenland, New Zealand) over the course of our series and were combined with an appropriate group based primarily on geography. A list of regions by respective number of observations has been included in Appendix A. Regional dummy variables were the same for both the real option and day rate model.

The variables we choose to add to Corts' model include an *accommodation capacity* variable, a region move count variable, and factor prices. The *accommodation capacity* variable is the maximum number of employees or laborers capable of staying overnight at a given rig. The *region move count* variable is the cumulative number of times a rig has moved between two regions prior to a given observations. Intra-regional moves, discussed previously, are capable of being longer or more expensive than certain inter-regional moves. Not always observable to the econometrician in our dataset, intra-regional moves and are not accounted for in our analysis.

Table 1: Descriptive statistics

	Cold Stacked	Age of rig	Shallow water	Deep water depth	Firm count	Firm count 2	Accommodation capacity	Region move count
No. of obs.	107571	107571	107571	107571	107571	107571	107307	107571
Mean	0.0541	23.7163	160.1515	1470.91	46.6011	11.7749	95.9383	0.3451
St. dev.	0.2263	9.5591	137.0941	2874.573	51.8387	11.0745	27.2656	0.7599
Min	0	0	0	0	1	1	29	0
Max	1	55	394	27000	174	44	220	12

Source: created by authors

Factor prices in the real option model are represented by the Brent spot price and its lags. A 36-month moving average price of the Brent spot price is also used. Brent was chosen over alternative benchmarks as the most common global reference price by both volume and frequency

(Fattouh, 2011). A moving average of Brent prices was also included due to the fact that previous research, most notably by Hamilton (2008) and Hooker (1996), found that crude oil spot prices, regardless of lag length choice, lose statistical significance as one adds data or lengthens a series. A 36-month moving average was chosen specifically since the three-year lag was the only statistically significant spot price lag when Brent was included in the real option model. Our initial lag length for Brent spot prices (2 years) was chosen as per the Box-Jenkins methodology (1970), while longer lags were included to adjust for current evidence from Ringlund et al. (2008) and Mauritzen (2014) who suggest that the only lags of any significance are between four and eight years.

4.2 Contract rate model data characteristics

We follow the literature (see, for instance, Kaiser and Snyder, 2013a; Osmundsen et al., 2012) and deflate the day rates as well as the factor prices using the US producer price index for oil and gas extraction industry. This allows us to eliminate the role of inflation and capture the real changes in the day rates as a function of real changes in underlying factors. While Kaiser and Snyder (2013a) investigate the effects of oil prices only, we follow the approach favored by Osmundsen et al. (2012) and take into account the effect of gas prices as well. The drilling rigs are used in the production of both resources and thus there is a certain degree of substitution that should be accounted for.

As the market for oil is integrated on a global level, we apply the same oil price, namely, Brent spot, to all regions due to the aforementioned reason. Gas markets, on the other hand, are regionalized and thus different regions demand different series of gas prices (Siliverstovs et al., 2005; Soderholm, 2000). We have matched the following gas prices to respective regions, as illustrated in the table below.

Table 2: The Series of Gas Prices (Indices) Matched with Regions

Gas price (index)	**Region**
Henry Hub, Close	US
UK Natural Gas Index (NBPI)	North Sea
IMF, Indonesian LNG, CIF Japan, End of Period	Australia/Asia and Southern Asia
IMF, Natural Gas, Russian, Border in Germany, End of Period	Europe and Russia, except North Sea

Source: created by authors

The series of gas prices (indices) are retrieved from the Macrobond database and are multiplied with regional dummy variables (dummies) to account for differences across markets. We assume that the gas prices in the regions that do not have a publicly available index are benchmarked to Brent spot prices.

To incorporate the factor prices in the model for offshore rig rates, we start with including both current and lagged values of oil and gas spot prices. This approach is consistent with Pesaran (1987) who pioneered the hypothesis that market participants have adaptive expectations when it comes to the factor prices – predictions about the future prices are based on past and present prices only. This assumption was proved to hold for the oil market (see, for example, a recent study by Alquist and Kilian, 2010). Similar to the real option model, we investigate the time series of the factor prices individually via the Box-Jenkins methodology to determine the number of lags (Box et al., 2008). Another approach to capture the effect of factor prices is to rely on the moving average of the series – a common practice to determine the trend of the market (Fabozzi et al., 2008). Hamilton (2008) provided support that coefficients up to the fourth lag are significant when investigating the formation of the oil price that is sampled in quarters. Ringlund et al. (2008) proposed using different smoothing parameters for different regions (the length of them varies from 3 to 24 months). We test 3, 6, 9, 12, 18, and 24 months moving averages to investigate which series has the highest explanatory power and compare it with the results obtained using lagged series to determine the most suitable approach.

Recognizing that the effect of the factor prices as well as of the utilization rates might be non-linear, we transform those variables as well as the day rates into the logarithmic form. The majority of the variables that proxy for rig and contract heterogeneity are dummies, while the maximum drilling depth and water depth are entered in logarithm form to account for possible non-linearities. Contract length and lead time are rescaled only by dividing by a factor of 1,000 for the ease of reporting.

5. Methodology

5.1 Real option model methodology

The model used by Corts (2008) predicts the decision rules that dictate when a rig will be cold stacked or reactivated via a real option framework. For each time period t, a rig owner will only stack rig i if the profits (π_{it}) and option value (Ω_{it}) are less than or equal to the present value of the reactivation costs (ω_{it}). Formally:

$$\pi_{it} + \Omega_{it} \leq S_{i,t-1} * \omega_{it} \qquad (1)$$

Where:

$S_{i,t}$ is the cold stacked indicator variable for rig i in period t taking a value of one if the rig is cold stacked and zero otherwise.

$S_{i,t-1}$ is the already-stacked indicator variable for rig i in period $t-1$ taking a value of one if the rig was previously cold stacked and zero otherwise.

π_{it} is equal to a rigs profits or the contract day rate minus operating costs

Ω_{it} is the difference in the present value of the expected profits conditional on having a rig either active in the market or cold stacked.

Note that if a rig was not stacked previously (i.e. $S_{i,t-1} = 0$), the left hand side of the inequality would only need to be less than or equal to zero. However, the major problem is that the elements required to estimate the variables in equation (1) are largely unavailable to the econometrician. Despite the examples provided in the introduction, operating and reactivation costs figures are limited at best, even amongst publicly traded rig management companies. For NOCs this kind of data is even scarcer. Furthermore, the requisite components of a real option estimate – perceived volatility, an appropriate spot price for our underlying asset, distribution assumptions, etc. – are complexities that while common to the real option applications (Günther, 2012; Dias, 2004), exceed the aims of our research efforts. To overcome those limitations, Corts utilizes rig and market wide proxy variables (presented in the data section of our paper) in order to examine what rig and market characteristics determine when cold stacking options are exercised.

Substituting these proxy variables into equation (1) results in Corts' baseline model that we test for robustness:

$$S_{it} = \begin{cases} 1 \; if \, \beta_1 X_{it} + \beta_2 Z_{it} - S_{i,t-1}\omega_{it} + \varepsilon_{itj} \leq 0 \\ 0 \;\; otherwise \end{cases} \qquad (2)$$

Where:

X_{it} is a vector of rig and firm specific characteristics.

Z_{it} is a vector of market wide characteristics.

ε_{itj} is a normally distributed (white noise) error term

This frames the cold stacking decision from equation (1) as a binary discrete choice model, which we will estimate using a paneled logistic regression. Given that the majority of the variables for rig and firm characteristics are constant over time, this model will best be estimated via a random effects model and will provide estimates as to the probability of a rig being cold stacked or reactivated given its previous status and selected market and firm characteristics. The econometric implications of a random effects model rest on the assumption that the explanatory variables are exogenous ($E\{X_{it}\varepsilon_{itj} = 0\}, E\{Z_{it}\varepsilon_{itj} = 0\}$ and $E\{\omega_{it}\varepsilon_{itj} = 0\}$). While potentially restrictive, the inclusion of appropriate time dummies will absorb any time-correlated variation that would otherwise be included in our error term. Huber-White standard errors are also used to deal with any potential homoscedasticity in our data (White, 1980).

We also find it reasonable to assume all of the variables used in our logistic regression can serve as proxies for reactivation costs and operational costs, and we therefore interact all variables with the dummy indicator variable $S_{i,t-1}$. For instance, rig age will *ceteris paribus* increase the cost of operating a rig. Older rigs will also be more expensive to bring up to current operational specifications when reactivated. Each variable could also be argued to have an effect on future expected profits (Ω_{it}) – as age increases, future potential profits drop and therefore option value should decline. This simultaneous effect of the proxies on both types of costs and option value is the basis of Corts' suggested test of whether variables from equation (2) are quantitatively better proxies for operational or reactivation costs. A brief summary of the theory is presented in the following paragraph. While it should be noted here that the majority of our own findings do not corroborate the inferences discussed, the hypotheses are nonetheless presented since option execution via rig and firm heterogeneity can still be determined from the model, just not to the same degree as presented in the following paragraph.

For instance, if increasing a variable like *age* had a negative effect on the operating profits of a rig manager, this could come from either increased operating costs or decreased option value (due in part to higher reactivation costs). Regardless of why, our expectations of the probability of a currently active rig being cold stacked will increase and so will the probability that a currently cold stacked rig will remain cold stacked as age increases. This shared sign direction of probabilities (be it positive or negative) for a given variable is indicative that, despite serving a proxy for reactivation costs, this variable is a better proxy of operating costs. However, if a variable serves as a better proxy for reactivation costs, the signs of the probabilities would go in opposite directions. This is due to the fact that higher reactivation costs would reduce the likelihood of activating a cold stacked rig and increase the likelihood that a currently active rig will be cold stacked.

We also account for the firm size to test potentially conflicting theories about its role in its cold stacking or reactivation behavior, i.e. whether larger firms are more likely to crowd out smaller firms via market power or would their economies of scale, which would lower reactivation costs and more easily retain labor, make reactivation and cold stacking a more likely event. If market power is the dominant market strategy, rig owners with the largest number of rigs would benefit the most from the increased day rates via more frequent cold stacking of active rigs and keeping already stacked rigs stacked. On the other hand, if lower reactivation costs and easier labor retention are more critical to firms' decision making, larger firms would still be more willing to stack rigs, but would also be more willing to reactivate rigs that are currently stacked.

While our results are conditional on more formal statistical results which are presented in subsection 6.1, our replication results of the Corts' model lead us to two important econometric issues. First, the interpretation of interaction coefficients in any non-linear model must account for both the variable type of the interacted terms as well as the non-linear estimation of the effect on a given interaction. Second, the utility of Corts' model may not be ideal for inferring the superiority of a given variable as a proxy for operational or reactivation costs. We suggest and test additional proxies in our own model specification.

5.1.1 Real option model re-specification

Our model adjustments include utilizing alternative proxy variables as well as the addition of market wide characteristics, most notably the inclusion of Brent crude prices or Brent crude price trends, in Z_{it}. Corts did not include factor prices. Instead he relied on region, month, firm, and firm-month dummy variables that would capture any market-wide time variation in his panel data. These dummies are included in order to eliminate any bias caused by serial autocorrelation of the ε_{itj} term in equation (2). However, his estimation ignores two critical issues. First, serial correlation could exist at the individual rig and not just the firm level[7]. Second, including a large number of dummies to absorb autocorrelation can cause a significant number of observations to be dropped from a given model. This is particularly problematic in binary choice models where perfect or near perfect collinearity is common for independent dummy variables (Farrar and Glauber, 1967).

While this doesn't automatically discount Corts' findings, the loss of more than half of Corts' data – resulting in an average of 14 monthly observations per rig – results in less efficient estimates. A small per rig sampling also makes these results vulnerable to small sample bias, which would then undermine the external validity of the results (Stock and Watson, 2003). Likewise, Corts' results may further suffer from selection bias due to the narrow time frame in which he examined the MODU market. The differences between the mean and standard deviation of our cold stacked variable – Corts' cold stacked indicator variable had a mean and standard deviation of 0.53 and 0.22 while our results were 0.054 and 0.22 respectively – lead us to believe that his series began or ended at an extreme value relative to the population mean. The inclusion of factor prices is therefore an attempt to minimize the number of dropped observations due to multicollinearity. By comparison, our smallest sample model still has an average of 96 observations per rig. We also wanted our model to test the empirical evidence (Ringlund et al.,

[7] This was addressed via a Cox proportional hazard model as the inclusion of firm, rig, month, and region dummies would be empirically impossible due to collinearity.

2008; Reiss, 1989) as well as anecdotal advice from industry professionals that factor prices and their trends are one of the most important determinants of rig activity.

Finally, we make three model specification changes to Corts' model that deserve highlighting. First, our definition of the rig count variable was broadened from the number of rigs per manager per region per month to the number of rigs per manager per month. Assuming that even small firms think globally seems appropriate given our own empirical knowledge of inter-regional rig movements and the prevailing belief of firms that the MODUs "operate in a single, global offshore drilling market <…> rigs are mobile assets and are able to be moved according to prevailing market conditions" (Transocean, 2013).

This was the same motivation for including a region move count variable as an alternative cost or option proxy variables. While alternative variables were available to us from our data provider, we opted for the latent region move count variable. This would efficiently capture unobservable rig heterogeneity and thus serve as a more appropriate and efficient proxy for cost and option values.

Thirdly, we include an *accommodation capacity* variable as an alternative measure of observable heterogeneity. While evidence suggests that staffing needs are heavily contingent on a rig activity – drilling versus accommodation, for example – accommodation capacity still provides with a measure of the maximum number of offshore laborers who would either be re-assigned or fired if a rig was cold stacked. If the economies of scale or labor retention theory presented in the previous section holds true, we would expect an increase in the probability for an active rig being cold stacked as well as an increase in the probability for cold stacked rigs being brought back into use.

5.1.2 Logit interaction terms and interpretation

Interaction terms are commonly used in econometric models to assess how the effect of one independent variable depends on the sign and coefficient of a secondary independent variable (Stock and Watson, 2003). This allows researchers to operate outside of the assumption of a standard linear regression that requires all other variables in a model to be fixed. In a multiple linear regression, the interaction effect can be directly interpreted as the coefficient in front of the interacted term or β_{12} in the equation below:

$$Y = \beta_0 + \beta_1 X + \beta_2 Z + \beta_{12} XZ + \varepsilon \qquad (3)$$

Statistical significance can also be measured via a standard t-test (Verbeek, 2012). However, when using the logit (cumulative normal distribution) model, the interpretation is not as straightforward. Recall the logit model is:

$$F(Y) = \frac{1}{1+e^{-(\beta_1 X+ \beta_2 Z+\beta_{12} XZ)}} \qquad (4)$$

The interaction effect, unlike in the linear regression, is not the constant cross derivative with respect to *X* and *Z*. Rather, the interaction or marginal effect is highly contingent not only on the reference or starting point but also on the type of variable used in the interaction. For example, if one of our variables is continuous while the other is a dummy variable, as is the case in our model, the interaction effect is the "discrete difference (with respect to *Z*) of the single derivative (with respect to *X*)" (Norton et al., 2004). Formally:

$$\frac{\Delta \frac{\partial F(Y)}{\partial X}}{\Delta Z} = (\beta_1 + \beta_{12})(F\{(\beta_1 + \beta_{12})X + \beta_2\} \\ * (1 - F\{(\beta_1 + \beta_{12})X + \beta_2\}) - \beta_1[F(\beta_1 X)\{1 - F(\beta_1 X)\}] \qquad (5)$$

The implication of the above equation is two-fold. First, the interaction effect cannot be directly estimated via β_{12}. Second, this interaction effect in probit/logit models has been shown to have a sign and standard error that vary significantly across the sample space. This is true regardless if one is considering logarithmic odds[8], as presented by Corts (2008), or marginal effects (see Williams, 2009; Norton et al., 2004; Ai and Norton, 2003)[9]. Even if the interaction term equals zero, our interaction effect is still non-linear and cannot be considered constant. Although this issue is not unique to Corts – according to Norton et al. (2004) this mistake is pervasive error across a wide spectrum of published empirical research – this creates interpretation issues that may limit the validity of any model using these types of interaction terms.

If both the standard interaction term and marginal effects are inappropriate, what then can be used as an appropriate estimate for the interaction terms in our model? While not an

[8]This is the default output for logit/probit models in *STATA*.
[9]The ability to carry out the estimates described by Ai and Norton (2003) or Norton et al. (2004) is currently unavailable in *STATA* for all but the simplest single variable paneled logit and probit models. Our models are therefore unacceptable candidates for the models presented therein.

undisputed preference (see Mood, 2010; Brambor et al., 2006), most researchers who avoid the error of direct coefficient interpretation favor the *average* marginal effect [of equation (5)] across a given variable (Verbeek, 2012; Powers, 2005; Ai and Norton 2003). Therefore, we will present both the logarithmic odds and the average marginal effects for all of our model specification and estimates.

5.1.3 A multinomial logistic framework

Despite our larger sample size and model improvements, the composite issues of interaction terms and the irreproducibility of the original author's work lead us to question the utility of the binary choice model in framing rig managers' decisions. As mentioned in the introduction, there are alternative statuses beyond an active or cold stacked rig. Rigs can undergo workovers, modifications, or inspections. These decisions better position rig owners to meet the needs of an existing or a new client. They can also be used for exploratory drilling (typically short term contracts), production (typically long term contracts), or even accommodation (Kaiser and Snyder, 2013a). The binary choice model forces all of these categories into an active or cold stacked category, where the multinomial logit model provides a random utility framework (see Verbeek, 2012, p. 228) to put structure on the various probabilities of each status. Since order is irrelevant, any one status can be used as a base from which to predict the probabilities of a rig switching status. While losing the option based interpretation presented previously, accounting for available additional information would allow estimating the effects of rig and firm heterogeneity on the whole spectrum of rig managers' options.

The one drawback to a multinomial model is the independence of irrelevant alternatives (IIA) assumption (McFadden, 1974). The IIA property suggests that the utility and therefore probability of any two alternatives, no matter how similar, are independent of all other alternatives. While the majority of rig statuses are unique, there is a case to be made in saying that some statuses, including workovers and modification[10] or exploration and drilling, are similar enough to violate IIA. Following the recommendations of Hausman and McFadden (1974) and Amemiya (1981) we will nest similar categories and compare the estimates of the non-nested

[10] Workovers are typically done on older rigs needing to be brought back up to specification to remain a part of a firm's active fleet. Modifications are generally done at the request of a client. However, by our data provider's own admission, these definitions overlap and vary by region.

model via the Hausman-McFadden test. A reduction in categories will continue until the estimates from our base and nested model are no longer equal or when the IIA can be said to no longer hold. Table 3 summarizes how we combined statuses in our multinomial model.

The only additions made to the multinomial model compared to the real option model were the inclusion dummy variables for NOCs, and OPEC countries. OPEC has been of particular interest in previous research as a potential cartel or oligopoly in oil markets (see Brémond et al., 2012; Griffin, 1985; Gatley, 1984) and the inclusion of these dummies was to test whether these market participants behaved any differently than non-NOC rig owners or non-OPEC countries. These would have been included in our real option model, but resulted in a non-convex maximum likelihood solution, and were therefore dropped.

Table 3: IIA Multinomial Rig Status Combinations

Status	Freq.	New Status	Freq.
Accommodation	447	Cold Stacked	5,824
Cold Stacked	5,824	**Drilling**	80,755
Drilling	76,277	*Modification*	10,425
Inspection	3,297	Ready Stacked	4,383
Modification	5,276	Accommodation	447
Production	1,181		
Ready Stacked	4,383		
Workover	5,149		
TOTAL	101,834	Total	101,834

Note: Statuses with similar fonts in Status column were combined in the New Status Column (i.e. drilling and production become drilling).

5.2 Contract rate methodology

To investigate the formation of rig rates and take advantage of our extensive panel dataset we base our methodology upon the model by Osmundsen et al. (2012) who utilized a non-linear random effects model. However, we initiate a few deviations from the benchmark paper.

First of all, we account for factor prices by including lagged values or moving averages of the oil and gas price series. Osmundsen et al. (2012) took advantage of the function of constant elasticity substitution and performed the grid search to estimate the smoothing parameter from the data in order to construct the price index. This was provided as an alternative to the standard approach of modeling the factor prices as stochastic process (Brownian motion being most common, see, for example, Postali and Picchetti, 2006). We rely on a simpler method to reduce the uncertainties surrounding the measure and thus the resulting standard errors. Using moving average and lagged values makes the results less sensitive to the assumptions behind modeling the series and thus allows for wider generalization and simpler interpretation.

Secondly, we do not set a benchmark of the high utilization rate (98% in the benchmark study) to capture non-linearities in the day rate-utilization nexus. The reason for this exclusion is lack of theoretical and empirical motivation behind this set-up.

Thirdly, we follow the approach by Köhn and Thanopoulou (2011) who investigated the freight rates. We cluster the determinants into macro, rig-specific, and contract-specific groups as well as estimate the pooled model at the end. From an interpretational point of view this helps us explain day rate formation from multiple angles (for example, how important is the macroeconomic environment ignoring the rig and contract specifics). This also allows us to utilize both panel data estimation techniques (fixed effects as well as random effects models). Osmundsen et al. (2012) relied on maximum likelihood estimation of the random effects model only. Due to low variability in the rig characteristics, the variables of interest could not be estimated using fixed effects model. Clustering the determinants into three categories allows us to mitigate this problem, as macro and contract specific variables show enough variability to be estimated. However, estimations of the rig as well as pooled models are performed using random effects model and thus the results should be interpreted carefully.

5.2.1 Estimation techniques

We start with a simple pooled ordinary least squares estimation as the base case scenario. However, the presence of individual heterogeneity in observational units that is constant over time makes the coefficients biased and inconsistent over time. Similar to the real option model, we estimate standard errors that are robust to heteroskedastic and autocorrelated disturbances (Hoechle, 2007). Further, to allow for individual unobserved rig heterogeneity and to benefit from the fact that we have panel dataset, we employ the random effects and fixed effects models. Random effects model relies on quasi-demeaned data and thus utilizes variation between the individual rigs. However, its unbiasedness is conditional upon the unobserved heterogeneity being uncorrelated with explanatory variables over time. The fixed effects model relaxes the latter condition, but fails to identify the effect of time-invariant explanatory variables and thus suffers from lower efficiency as compared to random effects model (Verbeek, 2012). We base our choice on which estimation technique is preferred for a given model on the results of the Hausman test (Hausman, 1978). The latter test checks for the consistency of the estimates and gives a decision rule on whether random effects model suffers from abovementioned bias.

In addition to estimating the random effects model using the feasible Generalized Least Squares (GLS) method developed by Baltagi and Wu (1999), as a robustness check we also estimate the model using the Maximum Likelihood Estimation (MLE). Compared to GLS, MLE has an additional restriction that the disturbances follow normal distribution (Breusch, 1987).

In the following subsections present the individual models as well as variables selected.

5.2.2 Macro model

Firstly, we estimate the day rates as a function of macroeconomic factors – one-month lagged utilization rates as well as lagged (or smoothed) oil and gas prices.

$$day\ rate_{i,t} = \alpha_0 + \alpha_1 util_{t-1} + \sum_{j=0}^{n} \beta_j\ oil_{t-j} + \sum_{k=0}^{m} \gamma_k\ gas_{t-k} + \varepsilon_{i,t}\ (6)$$

Where:

$\varepsilon_{i,t}$~ N(0, δ^2) and subscripts identify contract (i) and time (t).

5.2.3 Rig model

Secondly, we investigate the day rates from the hedonic price model perspective – how is the heterogeneity of rigs priced in the market?

$$day\ rate_{is,t} = \alpha_0 + \alpha_1 age_{s,t} + \alpha_2 cap_{s,t} + \alpha_3 cost_{s,t} + \alpha_4 wd_{s,t} + \alpha_5 dd_{s,t} + \beta' X + \varepsilon_{is,t} (7)$$

Where:

$\varepsilon_{i,t}$~ N(0, δ^2) and subscript *(s)* identify the rig and (i) the contract

X represents a vector of dummy explanatory variables that include the type of the rig (jackup, semisub or drillship), the competitive status (competitive versus not), whether the rig has moved to other region, the status of the active rig (drilling, in workover, used for accommodation or production), and whether the rig is classified as severe environment or not.

Taking into account the fact that rigs can be upgraded over time we also allow for variation in their features over time.

5.2.4 Contract model

The next issue worth investigation is how different features of the contract (ex. the lead time and contract length) are reflected in the price and whether NOCs pay different day rates compared to their non-NOC peers.

$$day\ rate_{i,t} = \alpha_0 + \alpha_1 lead_{i,t} + \alpha_2 length_{i,t} + \beta' X + \varepsilon_{i,t} (8)$$

Where:

$\varepsilon_{i,t} \sim N(0, \delta^2)$.

X stands for a vector of explanatory variables that define the type of well the contract is written on, i.e. whether it is a fixed well, term or well-to-well and whether it is for exploratory, development or appraisal well, whether the counterparty (the rig operator) is NOC, whether the contract has an embedded option and a proxy variable for the firm size to capture whether the rig managers exercise their market power when setting the rig rates.

We also introduce the dummy variables to control for the time and region specific effects.

6. Findings and interpretation

6.1 Real options

The first two columns of table 4 provide both the original estimates from Corts' paper as well as our replication of the same model. The trend is that, despite maintaining the signs (positive/negative) of our variables, there has been a loss of significance across every proxy variable presented except two: *already stacked* and the *age of rig* (for currently active rigs). As predicted by the real option model, the most significant predictor of a cold stacked rig is whether or not the rig was previously stacked. However, as noted earlier, the log likelihood estimates of all proxy variables have been interacted with the *already stacked* variable. A judgment as to the strength or efficiency of any of the proxy variables cannot be based solely on the coefficient estimates presented. Therefore, we present the average marginal effects of Corts' model in column 3.

In that respect, the only variable to maintain statistical significance is *already stacked*: an already stacked rig increases the probability of a rig remaining cold stacked by an average margin of 40.3%. Interestingly, the majority of our proxy variables average marginal effects are substantially smaller than our original estimates. While due in part to the small initial estimates, according to Powers (2005) this trend is indicative of sign change(s) for coefficient estimates [equation (5)] across the sample space of almost all our variables. The below discussion should be taken with the limitations of these interaction terms in mind.

Table 4: Real Option Panel Logit Table

	I Corts Original^	II Corts Redo	III Avg. MFX	IV Nominal Prices	V Avg. MFX	VI Trend Prices	VII Avg. MFX
Already Stacked	10.016*	18.49***	0.403*	10.76*	.005*	12.05***	.007**
	1.9558	8.45	2.16	2.47	2.32	5.35	3.45
If currently Cold Stacked							
Age	0.1634*	0.0231	0.00005	0.0362	0.00001	0.0289	0.000017
	0.049	0.33	0.31	0.53	0.53	0.62	0.63
Shallow Water Depth	-1.3813*	-0.00712	-0.00005	0.00198	9.91E-07	-0.000521	-3.06E-07
	0.298	(-1.43)	(-1.03)	0.35	0.35	(-0.11)	(-0.11)
Deep Water Depth	-0.0191*	-0.000223	-4.86E-07	-0.000684	-3.42E-07	-0.000381	-2.24E-07
	0.0304	(-1.15)	(-1.01)	(-1.76)	(-1.70)	(-1.60)	(-1.42)
Corts Firm Size	0.0359*	0.0199	0.00004				
	0.0155	0.79	0.72				
Firm Size				0.108*	0.00005*	0.0167*	9.81E-06*
				2.09	2.01	2.57	2.12
Accommodation Capacity				0.0272	1.36E-05	0.0118	6.97E-06
				0.62	0.62	0.58	0.56
Rig Move Count				-2.630***	-0.00131**	-2.499***	-0.00147***
				(-3.63)	(-3.20)	(-5.04)	(-3.55)
If currently Active							
Age	0.0999*	0.118**	0.0003	0.0515	0.00003	0.0791*	.00004*
	0.0488	2.67	1.32	1.5	1.45	2.36	1.97
Shallow Water Depth	-0.8038	-0.00479	-0.00001	0.00433	2.17E-06	0.00262	1.54E-06
	0.2374	(-1.31)	(-.94)	1.11	1.1	0.73	0.74
Deep Water Depth	-0.067*	-0.0000789	-1.72E-07	0.000233	1.16E-07	0.000195	1.15E-07
	0.0221	(-0.54)	(-.51)	1.58	1.52	1.31	1.24
Corts Firm Size	0.0999*	0.0134	0.00003				
	0.0147	0.7	0.65				
Firm Size				0.00466	2.33E-06	0.00429	2.52E-06
				1.42	1.38	1.25	1.19
Accommodation Capacity				-0.032*	-0.000016*	-0.0387**	-0.000022*
				(-2.31)	(-2.15)	(-2.94)	(-2.48)
Rig Move Count				0.327	0.000164	0.325	0.00019
				1.92	1.82	1.89	1.7
B				-0.00161	-8.05E-07		
				(-0.14)	(-.14)		
L12.B				-0.00255	-1.28E-06		
				(-0.24)	(-.24)		
L24.B				-0.00906	-4.53E-06		
				(-0.83)	(-.83)		
L36.B				-0.0226*	-.00001*		
				(-2.09)	(-1.97)		
L48.B				0.0111	5.53E-06		
				1.32	1.29		
L60.B				0.0265**	0.00001*		
				2.62	2.39		
3 Month Moving Average						0.0104	6.09E-06
						1.5	1.48
Rig Type Dummies	Yes	Yes		Yes		Yes	
Jointly Significant	Yes	No		Yes		Yes	
Month Dummies	Yes	Yes		n/a		n/a	
Jointly Significant	Yes	Yes		n/a		n/a	
Region Dummies	Yes	Yes		Yes		Yes	
Jointly Significant	Yes	No		No		No	
No. of observations	*15,129*	*107,533*	*107,533*	*63,919*	*63,919*	*106,491*	*106,491*

t statistics under coefficient estimates/ z statistics are under marginal effect columns
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ results with standard error under estimates. Copied from Corts(2012).

The model is re-estimated with our additional proxy variables as well as lagged crude oil prices and the results are presented in column 4 and the average marginal effects in column 5. Moving average crude prices are alternatively used and presented in column 6 with and the average marginal effects in column 7. Again, only the same two aforementioned variables are significant. While this negates our ability to distinguish operational versus reactivation costs as Corts did, there are some insights worth highlighting prior to discussing model alternative. Principally, the majority of our independent variables appear to predict cold stacking behavior for either already stacked or already active rigs, but not both.

A positive coefficient for firm size is indicative that larger firms are more likely to keep cold stacked rigs stacked. However, due to the insignificance of the firm size term for active rigs, little can be extrapolated regarding firm size and its effect on active rigs. Likewise, the more a rig has been moved across regions, the less likely it is to remain cold stacked. Unfortunately, the *rig move count* proves insignificant when discussing active rigs. This could be indicative that, while cold stacking of active rigs may be due to reasons not captured by the model, reactivation decisions are based on the specifications of rigs that are captured by how often a rig has been moved. *Accommodation capacity* has both a negative and significant coefficient estimate indicative that rigs capable of holding more personnel on board are less likely to be cold stacked. However, a similar statement cannot be made with respect to currently stacked rigs.

With respect to factor prices, lagged prices at 36 months and 60 months (three and five years respectively) are the only significant lags in our model. The estimates suggest opposite probabilities with regard to the either term: increases in the three-year lagged value decrease the probability a rig is stacked, where an increase in the five-year lagged value increases the probability a rig is cold stacked. Note that these terms are not interacted and account for the effect of crude prices on the entire rig fleet, active or cold stacked. As expected, the long-term prices rather than spot prices, matter significantly more to rig fleet managers. However, the positive probability for the five-year lag is counter-intuitive. One possibility is that firms are confident enough, when prices increase over the long term, to take rigs out of the market and increase their contract day rates. The trended factor price model tells a similar story, but lacks statistical significance. Alternatively, this could also be evidence of oil prices oscillating mean reversion on firm behavior, as suggested by Pindyck (1999).

The contrast between Corts' results as well as our own is most likely due to a combination of the aforementioned smaller sample size and the interaction term interpretation issue. One simple solution would be to, as with factor prices, estimate the model across the entire rig fleet, without interacting any of our terms against the rig's previous status. The nominal price specification of the real option model is estimated and presented in table 5. The significant proxy variables for cold stacking options by firms are similarly the already stacked, firm size, accommodation capacity, and five-year lagged factor price variables.

Table 5: Real Option Panel Logit Model 2

	I
Already Stacked	13.95***
	27.63
Age of Rig	0.0298
	0.87
Shallow Water Depth	0.0039
	1.09
Deep Water Depth	0.00006
	0.41
Quarter Capacity	-0.0313*
	(-2.44)
Firm Count	0.007*
	2.46
Region Move Count	-0.0828
	(-.26)
Brent	-0.0008
	(-.08)
l12. Brent	-0.0013
	(-.14)
l24. Brent	-0.0048
	(-.49)
l36. Brent	-0.0176
	(-1.79)
l48. Brent	0.0117
	1.44
l60. Brent	0.0213*
	2.15
Rig Type Dummies	Yes
Jointly Significant	Yes
Month Dummies	n/a
Jointly Significant	n/a
Region Dummies	Yes
Jointly Significant	Yes
No. of observations	*63,919*

The alternative to the real option model is the previously presented multinomial logit model. Including alternatives beyond cold stacking, these results are presented in table 6. Status alternatives were combined as indicated in table 3 to deal with the potential violations of the IIA assumption in a multinomial model. The Hausman-McFadden test comparing our nested and non-nested models indicates that the IIA assumption is not violated. Due to failing the same test, further reductions of categories could not be done. These findings call us to question the effectiveness of a binary choice real option model, which relied on two-status categorization (active versus cold stacked).

For ease of interpretation cold stacking was the base outcome chosen in the model. Despite the spatial variation of the signs and significance across categories, the results are more in line with Corts' findings and regain the significance lost in the real model specification. Interestingly, age remains predominantly an insignificant predictor of rig status except for accommodation (i.e. as rigs age they are less likely to be used for accommodation versus being cold stacked). Similar to Corts' findings, rigs capable of operating deeper, both at the *shallow water depth* and *deep water depth,* are generally more likely to be kept cold stacked versus most alternatives. This could be indicative that more highly specified rigs are generally not crowding out lower specified ones as proposed in the introduction, and that they are kept cold stacked longer barring functional or contractual necessity.

Table 6: Multinomial Logit Model Estimates (Cold stacked Base Outcome)

	Accommodation	Drilling	Modification	Ready Stacked
Already Stacked	-24.67	-15.58***	-12.60***	-13.17***
	(-0.02)	(-20.17)	(-22.37)	(-12.31)
Age of Rig	-0.0613*	0.013	0.0109	0.0295
	(-2.20)	0.49	0.41	1.11
Shallow Water Depth	0.00305	-0.00432	-0.00936*	-0.0106**
	0.8	(-1.17)	(-2.53)	(-2.87)
Deep Water Depth	-0.000283**	-0.000148*	-0.000123	-0.000495***
	(-3.17)	(-2.12)	(-1.75)	(-6.80)
Accommodation Capacity	-3.458***	0.376	0.212	-0.801
	(-3.56)	0.49	0.28	(-1.04)
Firm Count	2.083	0.625	0.1	1.271
	1.92	0.58	0.09	1.18
Region Move Count	0.0680***	0.0691***	0.0550***	0.0679***
	5.86	6.21	4.93	6.08
NOC Rig Owner Dummy	-0.00875**	-0.00326	-0.0139***	-0.00817**
	(-2.76)	(-1.10)	(-4.68)	(-2.73)
OPEC Dummy	-16.65	0.482	-0.295	-0.0348
	(-0.02)	0.63	(-0.39)	(-0.05)
Jackup	1.973**	-0.445	-1.157	-0.121
	3.01	(-0.69)	(-1.80)	(-0.19)
Semisub	-1.750*	2.998***	3.559***	1.726*
	(-2.17)	4.03	4.77	2.3
Drillship	-1.436	-0.127	-0.651	-1.345
	(-1.43)	(-0.13)	(-0.68)	(-1.40)
Brent	-13.97	0.441	0.878	2.16
	(-0.02)	0.28	0.55	1.34
l12. Brent	-0.0083	0.00311	0.00195	-0.00459
	(-0.81)	0.32	0.2	(-0.47)
l24. Brent	-0.00938	0.00627	0.00749	0.00225
	(-1.01)	0.71	0.85	0.25
l36. Brent	0.0218*	0.0125	0.0155	0.0121
	2.22	1.34	1.65	1.28
l48. Brent	0.000845	-0.0135	-0.00933	-0.0111
	0.09	(-1.54)	(-1.06)	(-1.26)
Number of Observations		***62,797***		

t statistics below coefficient estimates

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Region move count is the only variable universally significant across categories. The *region move count* variable indicates that the more a rig is moved, the more likely it is to no longer be cold stacked. Otherwise, if the rig is owned by a NOC, the probability of a cold stacked rig being utilized for anything, except drilling, is negative. This could also be indicative of inefficient or under-utilization from NOC with regards to their MODU fleet (Kaiser and Snyder, 2013a). On the other hand, OPEC countries seem to behave no differently than non-OPEC countries, but given that most OPEC countries have more than just their own NOC operating MODUs, this should come as little surprise.

The rig type dummies also highlight some interesting MODU market characteristics. Primarily, semisubs are more likely to be reactivated for anything except accommodation work. For jackup rigs, the exact opposite is true, and rigs are more likely to be used for accommodation work relative to being cold stacked. Factor prices are now generally insignificant. Trends were not included in the table, but were also found to be insignificant. Given the stated importance of factor prices this is again surprising, but the evidence indicates the majority of rig decisions are based more on firm and rig characteristics and less on exogenous macroeconomic factors. Whether this also holds true for the contract day rates earned by active rig owners will be presented in the results of our day rate model below.

6.2 Formation of the day rates

6.2.1 Macro model

Estimation of the macro model with respect to different specifications reveals the following results[11]. Firstly, the elasticity of the day rate with respect to the one-period lagged utilization rate is equal to 1.13 if factor prices are not accounted for (see column 1 in table 7). If

[11] The estimation was performed using the fixed-effects regression for all models except the one reported in column 6 (for which random effects estimation was used), as the Hausman tests (not reported) indicate that there are significant differences between the coefficients from the fixed effects and random effects regressions. Thus the coefficients from the random effects regression suffer from the bias due to presence of unobserved heterogeneity being correlated with the explanatory variables.

we include the moving average 18-month series for oil and regionally matched gas prices[12], the effect of the utilization rate increases to 2.49 indicating that in the short run the supply of the offshore rigs is inelastic and thus small changes in the utilization rates translate into substantial variations in the day rates (see column 4). In line with the evidence provided by Osmundsen et al. (2012), the development of the oil price has significant positive effect on the day rates – an increase in the 18-month moving average of the oil price by 1% implies increase in the day rates by 0.77% holding the effect of gas prices constant.

Table 7: Results of the Macro Model

	I Day rate	II Day rate	III Day rate	IV Day rate	V Day rate	VI Day rate	VII Day rate	VIII Day rate
Util (t-1)	1.127***		2.507***	2.487***	3.013***		2.952***	2.963***
	(11.05)		(21.97)	(22.10)	(10.41)		(9.88)	(9.85)
Oil (MA)		0.344***	0.821***	0.766***		0.577***	0.176	0.237
		(7.00)	(18.20)	(14.86)		(3.77)	(1.19)	(1.56)
HH (MA)		-0.136**		-0.131***		0.0792		0.0937
		(-3.29)		(-3.57)		-1.51		-1.77
IndJap (MA)		-0.0412		-0.0695*		-0.106		-0.129
		(-1.28)		(-2.15)		(-1.50)		(-1.76)
NBP (MA)		0.0835**		0.0404		0.0456		0.0212
		(3.10)		(1.61)		(1.30)		(0.57)
Russian (MA)		0.266		0.222*		0.884*		0.509***
		(1.81)		(2.55)		(2.01)		(3.82)
_cons	11.06***	9.675***	8.749***	8.956***	11.09***	8.872***	10.53***	10.27***
	(433.21)	(58.88)	(65.79)	(55.70)	(115.69)	(18.25)	(21.68)	(20.23)
Time controls	No	No	No	No	Yes	Yes	Yes	Yes
Regional controls	No	No	No	No	Yes	Yes	Yes	Yes
N	5156	5156	5156	5156	5156	5156	5156	5156
R^2	0.045	0.074	0.221	0.229	0.427	0.2434	0.427	0.429

t statistics in parentheses

$^{*}p$<0.05, $^{**}p$< 0.01, $^{***}p$< 0.001

[12] The inclusion of the lagged values selected via Box-Jenkins methodology provided less superior results in terms of the explanatory power as well as easiness of interpretation compared to the usage of moving average series. When it comes to the period during which the moving average should be estimated, the 18-month period produces the most significant estimates of the coefficients in front of the oil prices and thus this period is applied to all factor prices.

However, in contrast with abovementioned research, oil price has more substantial influence compared to the gas prices. This might be the case because we look at the rig market on global level and thus the oil price is more widely accepted determinant by the decision makers at this level. At the same time, during the period of analysis substantial supplies of shale gas came into the US market and thus the drilling for offshore gas has dwindled[13]. According to EIA (2013), the share of non-associated offshore gases in US as of total has decreased from 21% in 2000 to slightly less than 6% in 2013, while during corresponding period the share of shale gas increased from 2% to 36%. In fact, the coefficient in front of the Henry Hub prices is negative (-0.13) and significant even at 0.1% significance level. This shows that during the period of analysis rig operators had to be incentivized to rent the offshore rigs despite increasing gas prices and thus possibilities to reallocate their production towards unconventional gases.

Including time- and region-specific[14] dummy variables together with utilization rates and factor prices (see column 8) shows that the elasticity of the day rates with respect to utilization rates increases to 2.96. The factor prices appear to be insignificant except for the Russian Natural Gas (Border in Germany) moving average price series. Increase in the latter by 1% induces an increase in the day rates by 0.51%. This indicates that the production substitution effect is highest in the European-Russian region (except for the North Sea) and there was little decoupling of the gas prices from the oil prices. This is not surprising, as in 2012 more than 80% of the natural gas prices were indexed to the price of oil products (Erdős and Ormos, 2012). Thus our analysis shows that once utilization, regional and time specific effects are accounted for, the gas and oil prices do not have a significant effect on the day rates.

6.2.2 Rig (hedonic) model

Further, we investigate how the rig heterogeneity is priced in the market[15]. As hypothesized in the descriptive statistics, the type of the rig is important determinant of the day

[13] Note that 34% of the contracts investigated (1,864 out of 5,543) are for the US region.
[14] Initially we have also included the dummy variable differentiating between OPEC and non-OPEC countries instead of regions. The coefficient was insignificant across all specifications, thus we relied on individual regional dummies onwards.
[15] The estimations of the rig model were performed using random effects estimator, because the rig characteristic do not vary substantially over time and thus it is not possible to estimate the coefficients using the fixed effects model. Therefore, the precision and magnitude of the coefficients might be questionable, as the problem of unobserved rig heterogeneity being correlated with explanatory variables remains.

rates. After controlling for the regional and time effects, the drillships and semisubs demand a 21.6% and 21% higher premium respectively compared to jackups (see column 2 of table 8). Moreover, *maximum water depth* is both significant and substantial determinant of the rig rates (in contrast to *maximum drilling depth*) – one % increase in the *maximum water depth* translates into a 1.65% increase in the day rate. Similar to the latter variable is the dummy indicator on whether the rig is classified as severe environment or not. The rig operators pay a premium of 11.3% for this type of rig due to more advanced technical capabilities and increasing demand for rigs able to drill in remote locations.

When it comes to the rig's operational status, the rigs contracted for offshore accommodation are priced almost 24% less compared to the drilling rigs, while those operating under workover and production statuses are priced 11.4% and 8.3% less. Finally, as postulated by Osmundsen et al. (2012), age is an important determinant of the day rate charged. After 10 years, the day rate earned by a rig declines by 8.5%, all else held constant.

Table 8: Results of the Rig Model

	I **Day rate**	**II** **Day rate**
Moved Across Regions	0.171***	0.0939***
	(6.47)	(4.35)
Competitive	0.0923**	0.03
	(2.69)	(1.11)
Drillship	0.231***	0.216***
	(3.76)	(4.42)
Semisub	0.264***	0.210***
	(5.46)	(6.65)
Max Water Depth	1.331***	1.653***
	(9.50)	(17.56)
Max Drilling Depth	0.95	1.45
	(1.61)	(1.31)
Workover	-0.135***	-0.114***
	(-4.31)	(-4.66)

Accommodation	-0.221***	-0.235***
	(-3.94)	(-3.73)
Production	-0.229***	-0.0825***
	(-29.42)	(-3.78)
Rig Age	-0.00908***	-0.00846***
	(-7.70)	(-6.64)
Accommodation Capacity	0.00420***	0.00301***
	(6.52)	(4.93)
Severe Environment	0.242***	0.113***
	(6.85)	(3.52)
Construction Costs	(0.00)	(0.00)
	(-0.59)	(-1.26)
_cons	5.776***	4.18
	(4.22)	(1.64)
Time controls	No	Yes
Regional controls	No	Yes
N	5087	5087
R^2(overall)	0.6491	0.7823

t statistics in parentheses

*p< 0.05, **p< 0.01, ***p< 0.001

Interestingly, estimating the model with regional and yearly dummies reveals that the offshore rigs in the North Sea region earn significantly higher day rates compared to most of the regions. The most pronounced difference is vis-à-vis the US region (coefficient is -0.42, i.e. if the offshore rig is contracted in the US, the day rate paid is 42% lower compared to the rig with the same specifications contracted in the North Sea). This reflects a more intense competitive environment in the US region as well as, possibly, the inflated costs in the North Sea region compared to other offshore rig markets.

If we relax the controls for the time and region specific effects, the signs and significance of the coefficients does not change, while their magnitude varies (see column 1).

Finally, the indicator variable on whether the rig is mobile (was moved across the regions) shows that rigs earn on average almost 10% more if moved from one region to the other after controlling for time and regional effects. This can be interpreted from two perspectives. Firstly, the managers of the rigs incur substantial costs when transporting the rig from one location to another and thus have to be compensated for that. Therefore, the coefficient serves as a proxy for the size of the costs incurred. On the other hand, as noted by Kaiser and Snyder (2013a), the offshore rig market could be characterized as regional. As a result rig managers that can move rigs from one region to another can exploit the discrepancies in prices. The coefficient could alternatively be interpreted as the size of existing arbitrage profits.

6.2.3 Contract model

The third[16] – contract specific – model can be summarized as follows. If we do not include regional and time dummies (see column 2 of table 9), the magnitude of the lead time has a positive effect on the day rates (extending the lead time by 100 days induces increase in the day rates by 1.1%). This positive premium to the lead time reflects the operators' willingness to pay for reduced risk of having to contract the rig later when the start of the drilling is due. *Contract Length,* on the other hand, is not significant at 1% in any of the specifications, thus we find no support for the hypothesis raised by Kaiser and Snyder (2013a) that there exists a long-term contract premium[17].

[16]The estimates were obtained using the fixed effects model, as Hausman test indicates that the error term suffers from correlation with unobserved heterogeneity in the rigs that is constant over time.

[17] Kaiser and Snyder (2013a) have group the contracts into longer than the mean and shorter than the mean average categories with respect to the contract length. Afterwards, they compared respective day rates. We, on the other hand, make use of all information we have regarding the contract length and include it as one of the explanatory variables in the econometric model that is of log-linear specification vis-à-vis *contract length*.

Table 9: Results of the Contract Model

	I	II	III	IV
	Day rate	**Day rate**	**Day rate**	**Day rate**
NOC	0.0788**	0.03	(0.00)	(0.01)
	(2.68)	(0.93)	(-0.11)	(-0.55)
Lead	0.131***	0.114***	0.0741**	0.0828**
	(4.09)	(3.46)	(2.80)	(3.07)
Contract Length	0.0607*	0.0546*	0.02	0.01
	(2.49)	(2.24)	(0.93)	(0.52)
Option	-0.0721***	-0.0768***	(0.02)	(0.03)
	(-3.45)	(-3.64)	(-1.03)	(-1.62)
Term	0.104***	0.0973***	0.0786***	0.0775***
	(4.22)	(3.94)	(3.90)	(3.86)
Well-To-Well	(0.01)	0.01	0.16	0.16
	(-0.06)	(0.08)	(1.09)	(1.10)
Development	0.00	0.01	(0.00)	(0.00)
	(0.13)	(0.73)	(-0.25)	(-0.20)
Exploratory	0.0620**	0.0652***	0.0457**	0.0432**
	(3.21)	(3.46)	(2.91)	(2.70)
_cons	10.68***	10.72***	11.14***	11.12***
	(576.07)	(307.74)	(26.48)	(26.19)
Rigs owned	No	Yes	No	Yes
Time controls	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
N	3704	3555	3704	3555
R^2	0.045	0.071	0.379	0.383

t statistics in parentheses

*p< 0.05, **p< 0.01, ***p< 0.001

If the contract has an embedded option, then the day rate charged is 7.7% lower compared to the one without options. The effect is both economically and statistically significant. The embedded option in the contract allows for an extension of the contract (although not necessarily at the same terms as initial one). Information about the terms of extension is not available to us, only whether the contract has the option features. The option concerns the operators and not the rig owners. Thus the negative coefficient reflects the economic reality – the operators accept the lower payment in exchange for a possibility (yet not a guarantee) of future work or, compared to their competitors, more work. Furthermore, our estimates reveal that if the counterparty is NOC, it does not pay significantly higher day rates compared to Independent Oil Company (IOC) holding other features of the contract constant. This evidence is in contrast with the ownership premium hypothesis put forward by Kaiser and Snyder (2013a) that in addition to economic drivers, political ones influence the decisions made by NOCs and thus the companies of latter type end up paying higher price for the lease of rigs.

Also, we infer that the rig managers, on average, do not exert their market power when setting the day rates[18]. This is in line with evidence provided by Kaiser and Snyder (2013a). Quite the opposite – larger firms operating in the US region that represents the biggest and most liquid market for leasing offshore rigs charge lower day rates compared to their smaller competitors. The coefficient in front of the firm size is negative and statistically significant, yet is of relatively small magnitude – a firm owning 10 more rigs sets a 2% lower day rate. This provides evidence that companies owning more rigs are motivated by economies of scale rather than increased market power.

Including the regional and time controls and re-running the model returns insignificant coefficients in front of the option dummy variable (see column 4). The *lead* is, on the other hand, still statistically significant, yet by a lower magnitude (0.08 instead of 0.11).

6.2.4 Macro-rig-contract model

In the final model we combine all the variables into a pooled model[19]. The variables of interest retain their signs and significance, while the explanatory power of the model increases to around 80%. Once the regional and time specific controls are included (see column 2 of table 10),

[18] We start with including a numerical variable reflecting how many rigs the rig manager owns. It provides a proxy for the firm size. However, the initial estimations reveal that this is not significant determinant of the day rates. Further, we interact the firm size variable with regional dummies to account for the fact that market power is likely to be exercised on a regional rather than global level (results for individual dummies not reported). Note that inclusion of interaction terms and further inclusion of regional dummies makes the explanatory variables subject to the problems of multicollinearity, thus it is not surprising that interaction terms discussed above lose their significance once the stand-alone regional dummies are included (ex. in the specification presented in column 4).

[19] The estimates were obtained using the random effects model due to low intra-variability in the rig parameters.

the coefficient in front of the utilization rate reaches 3.17 (in the pure macro model it was 2.92), while the one in front of the Russian Natural Gas border price in Germany increase to 0.35, i.e. 1% increase in the 18-month moving average of the Russian Natural Gas prices results in 0.35% increase in the day rates earned by the rigs operating in the European and Russian regions (excluding the North Sea and Mediterranean).

The coefficients obtained from estimating the pooled model are somewhat higher compared to the ones in the rig model, but the differences are relatively small. For example, the rigs that were moved across regions demand 10% higher day rates compared to the ones who did not (while after estimating the contract model the respective figure was found to be 9.4%) and the drillships and semisubs earn slightly higher day rates compared to jackups. Interestingly, the day rates for the rigs contracted for accommodation purposes are estimated to be 33.4% lower compared to drilling ones (while previously this was found to be 23.5% lower). The coefficients in front of the *maximum water depth*, *drilling depth*, *rig age*, *accommodation capacity*, and *severe environment* variables were found to have similar effect as in previous specifications.

Finally, the explanatory variables that enter the contract model retain their signs and significance in the macro-rig-contract model, except for the lead time and dummy variable indicating whether the contract has embedded options. The coefficient in front of the lead time is small in magnitude and significance in the combined model (0.06 instead of 0.07), while the embedded options seem to have no effect on the day rates.

Table 10: Results of the Macro-Rig-Contract Model

	I **Day rate**	**II** **Day rate**	**III** **Day rate**	**IV** **Day rate**	**V** **Day rate**	**VI** **Day rate**
Util (t-1)	1.787*** (13.80)	3.171*** (10.20)				
Oil (MA)	0.590*** (12.25)	0.20 (1.14)	0.226*** (4.99)	0.268*** (5.82)	0.487** (2.77)	0.481** (2.64)
HH (MA)	(0.05) (-1.26)	0.06 (1.04)	-0.100*** (-3.68)	(0.02) (-0.37)	0.04 (0.78)	0.03 (0.63)
IndJap (MA)	(0.03) (-1.11)	-0.164* (-2.46)	0.03 (1.83)	(0.01) (-0.38)	-0.146* (-2.23)	-0.136* (-2.06)

NBP (MA)	0.0958***	(0.02)	0.0820***	0.106***	0.01	0.01
	(5.78)	(-0.50)	(8.29)	(6.86)	(0.40)	(0.39)
Russian (MA)	0.19	0.347***	0.282***	0.32	0.763***	0.374***
	(1.24)	(4.10)	(4.73)	(1.57)	(4.10)	(4.24)
Moved Across Regions	0.125***	0.1000***	0.132***	0.127***	0.106***	0.103***
	(5.35)	(4.68)	(5.30)	(5.00)	(5.00)	(4.71)
Competitive	0.01	(0.00)	(0.03)	(0.03)	0.01	(0.01)
	(0.38)	(-0.11)	(-0.86)	(-0.85)	(0.34)	(-0.32)
Drillship	0.220***	0.219***	0.228***	0.226***	0.244***	0.229***
	(3.55)	(4.08)	(4.05)	(3.64)	(4.77)	(4.31)
Semisub	0.226***	0.218***	0.235***	0.231***	0.234***	0.223***
	(5.29)	(5.87)	(6.42)	(5.46)	(6.94)	(6.23)
Max Water Depth	1.617***	1.752***	1.569***	1.619***	1.671***	1.731***
	(12.25)	(16.45)	(13.66)	(12.54)	(17.04)	(16.89)
Max Drilling Depth	1.74	1.66	1.479*	1.664*	1.81	1.78
	(1.95)	(1.61)	(2.20)	(2.24)	(1.74)	(1.66)
Workover	-0.107***	-0.0949***	-0.141***	-0.141***	-0.0884***	-0.0968***
	(-3.83)	(-3.70)	(-4.38)	(-4.40)	(-3.32)	(-3.53)
Accommodation	-0.229**	-0.334***	-0.293***	-0.266***	-0.337***	-0.349***
	(-3.11)	(-4.56)	(-3.87)	(-3.53)	(-4.30)	(-4.47)
Production	-0.202***	-0.171***	-0.216***	-0.204***	-0.127***	-0.121***
	(-7.77)	(-5.33)	(-8.59)	(-7.60)	(-4.38)	(-3.85)
Rig Age	-0.00858***	-0.00943***	-0.00839***	-0.00902***	-0.00892***	-0.00958***
	(-6.30)	(-7.34)	(-6.65)	(-6.82)	(-7.03)	(-7.37)
Accommodation Capacity	0.00308***	0.00255***	0.00312***	0.00304***	0.00273***	0.00276***
	(4.15)	(4.07)	(4.53)	(4.19)	(4.57)	(4.42)
Severe Environment	0.132***	0.0900**	0.132***	0.115***	0.105**	0.0942**
	(3.94)	(2.70)	(3.88)	(3.43)	(3.21)	(2.84)
Construction Costs	-0.000288*	-0.000312**	(0.00)	-0.000321*	-0.000290*	-0.000356**

	(-2.00)	(-2.62)	(-1.84)	(-2.36)	(-2.45)	(-2.96)
NOC	-0.0563*	-0.0503*	(0.04)	-0.0485*	(0.04)	-0.0537*
	(-2.40)	(-2.30)	(-1.86)	(-2.01)	(-1.83)	(-2.46)
Lead	0.07	0.0612*	0.0910**	0.109**	0.0504*	0.0600*
	(1.88)	(2.53)	(2.80)	(3.26)	(2.12)	(2.49)
Contract Length	0.02	(0.01)	0.02	0.02	(0.01)	(0.01)
	(0.76)	(-0.69)	(0.90)	(1.02)	(-0.48)	(-0.73)
Option	(0.03)	(0.02)	-0.0642**	-0.0686***	(0.01)	(0.03)
	(-1.66)	(-1.08)	(-3.14)	(-3.36)	(-0.72)	(-1.29)
Term	0.0950***	0.0867***	0.111***	0.108***	0.0897***	0.0886***
	(4.28)	(4.67)	(5.04)	(4.92)	(4.86)	(4.75)
Well-To-Well	0.08	0.16	0.08	0.07	0.15	0.15
	(0.67)	(1.23)	(0.63)	(0.61)	(1.06)	(1.12)
Development	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
	(-1.04)	(-1.02)	(-0.61)	(-0.36)	(-0.57)	(-0.77)
Exploratory	0.0430*	0.0329*	0.0632***	0.0609***	0.0420**	0.0388*
	(2.45)	(2.21)	(3.46)	(3.34)	(2.81)	(2.54)
_cons	2.11	4.23	3.511*	2.90	2.00	2.10
	(1.02)	(1.77)	(2.24)	(1.68)	(0.83)	(0.85)
Rigs owned	Yes	Yes	No	Yes	No	Yes
Time controls	No	Yes	No	No	Yes	Yes
Regional controls	No	Yes	No	No	Yes	Yes
N	3494	3494	3640	3494	3640	3494
R^2(overall)	0.7557	0.8145	0.7288	0.7368	0.8056	0.808

t statistics in parentheses

*p< 0.05, **p< 0.01, ***p< 0.001

6.2.5 Robustness checks

We re-estimate the models via a maximum likelihood estimation (MLE) instead of generalized least squares (GLS). The coefficients obtained are virtually the same with a few exceptions. The maximum drilling depth appears to have positive and significant (already at 1% significance level) effect on the day rates after including time- and region-specific dummy variables. Secondly, the coefficient in front of the dummy variable indicating whether the counterparty is the NOC or not is not significant in any of the specifications (with or without controls), while that in front of the contract length is. *Contract length* is 0.13 with no controls and 0.08 once time and region specifics are accounted for. Moreover, the contracts that have embedded options are significantly different from the ones that don't (have lower day rates) in both specifications.

Finally, in our pooled model, *maximum drilling depth* retains its significance under all specifications when estimating it with MLE. In addition to this, *lead* time seems to be statistically significant, yet an economically negligible driver behind the day rates after estimating the model with MLE as compared to GLS.

7. Concluding remarks and discussion

The purpose of our paper was to empirically investigate the factors driving both rig idling behavior and contract day rates for active rigs in the MODU market. To accomplish this, we utilized existing frameworks coupled with a larger series: a dataset spanning the global offshore rig market. We have also provided, where possible, an econometric based inquiry as to why our results may have differed from the original authors' work. In addition to this, we have revised the explanatory variables to be included and econometric techniques to be employed.

In the case of the real option model, we find the result variations are a matter of both econometric interpretation and sample size. Still, the real option model presented indicates that an already stacked indicator variable as well as firm size and rig move counts may be the best predictors of cold stacking behavior for currently stacked rigs. Accommodation capacity was the best predictive variable of cold stacking for currently active rigs, with higher capacity rigs being less likely to be stacked. This lends strength to the argument made by Corts that labor retention may be a commanding factor for rig managers. Future research may be better able to proxy for labor pooling for individual rigs or firms and to understand the actual effect of labor on idling decision. For the rig fleet as a whole, lagged factor prices are also shown to influence cold stacking behavior, but by a factor much smaller than was expected.

Given the potential econometric issues presented, we also suggest the use of a multinomial logistic model, which more accurately reflects the choices faced by rig owners and takes full advantage of available data. With no interaction terms in our new model, the majority of rig characteristics regain their expected signs and significance. However, factor prices lose their significance in this new framework. The effect of alternative specifications for factor prices (i.e. stochastic modeling) and their effect on the results presented would be one avenue we leave to future research. The rig move count variable is our only variable to maintain significance across all rig option alternatives. We expect that this is most likely due to the large amount of heterogeneity not captured by the variables presented in our model[20]. This leads us to conclude that latent variables such as rig move counts and firm size may be the superior predictors of cold stacking behavior. As our strongest latent variable, future research into the effect of observable rig characteristics on rig movements would further help to understand the scale of unobserved heterogeneity in the MODU market.

When investigating the determinants of the day rates, we have clustered the factors into macro, rig- and contract-specific. One-period lagged utilization rates were the only substantial and significant predictor of the day rates in the macro model after including factor prices (both oil and gas) as well as regional and time controls. Long build times and substantial costs of new rigs imply that in the short run the supply of the rigs is inelastic and thus the day rates are very responsive to the short-term fluctuations in demand. Our relatively large coefficient obtained in front of the lagged utilization rates supports this proposition.

We have also quantified the differences between the day rates charged for jackups, semisubs and drillships. The latter type of rigs demands significantly higher day rates compared to jackups, while, as expected, newer rigs that are able to operate in deeper waters, severe environment and have greater accommodation capacity earn more. Having extensive dataset covering the global market, we are the first ones to draw the attention to the mobility of the rigs – rigs that are contracted in different region compared to initial one earn around 10% more compared to units that stay in the same region. Moreover, offshore rigs in the North Sea earn significantly larger day rates when benchmarked to the rigs operating in other regions. These two insights give support for treating the offshore rig markets as regional. At the same time, they open avenues for further research on the trend towards the globalization of the offshore rig market as well as barriers that could slow or stop this process.

[20] Testing alterative rig characteristics not explicitly described in our paper did not change the rig move count estimates. Alternative rig characteristic tests and results are available on request.

The last cluster of our determinants of interest relates to the contract specifications. We show that the lead time has a positive effect on the day rate, while we find no support for the long-term contract premium hypothesis. Contracts with embedded options have, as expected, lower day rates and valuation of those options as stand-alone financial instruments is an interesting direction for future research. When it comes to the contract counterparties, NOC (that are renting out the rig) do not seem to overpay for the rigs compared to IOC. Firms that are leasing the rig seem to set the rig rates based on economies of scale rather than the market power considerations.

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Appendix A

Region	**Number of obervations**
Africa other	116
Africa west	1,475
Asia-Caspian	97
Asia, Far East	689
Australia-Asia	1,029
Southern Asia	2,040
Europe-Russia	138
North Sea	2,413
Mediterranean	507
Canada	150
Mexico	562
US	7,290
South America	1,234
Middle East	1,571