FLEXIBLE RESOURCE ALLOCATION STRATEGIES: RESOURCE REDEPLOYMENT AND RESOURCE IDLING

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Abstract

Resource redeployment and resource idling are two important resource allocation strategies that have always been considered separately from each other. This study develops a formal model that demonstrates that resource idling is an important precursor to resource redeployment. Not only does idling directly increase the use of redeployment but it also significantly enhances the effects of the inducement and cost to redeploy, which are two key determinants of redeployment. These theoretical predictions are tested with data on oil wells drilled in Texas over 25 years. The resource that can be idled and redeployed in this context is the rig owned by an oil-drilling contractor. Empirical analyses corroborate the theoretical predictions and demonstrate that the results are economically meaningful. In addition, the study demonstrates the biases that exist when redeployment is considered separately from idling.

Keywords: resource allocation, resource redeployment, resource idling, real options, oil-drilling industry.

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INTRODUCTION

Allocation of firms' resources is a core managerial function that is fundamental to strategic management (Bower, 2016; Maritan and Lee, 2017) and that is realized by firms through the use of various real options (Trigeorgis, 1996). One option that firms can apply to allocate resources is resource redeployment, or the withdrawal of resources from one use and switching them to another use. How firms change the allocation of resources through redeployment has been assessed in many theoretical studies (Feldman and Sakhartov, 2021; Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010; Lieberman, Lee, and Folta, 2017; Sakhartov, 2017; Sakhartov and Folta, 2014; 2015) and has been examined in substantial empirical research (Anand, 2004; Anand and Singh, 1997; Chang and Matsumoto, 2022; Dickler and Folta, 2020; Giarratana and Santaló, 2020; Miller and Yang, 2016; Morandi Stagni, Santaló, and Giarratana, 2020; O'Brien and Folta, 2009; Sohl and Folta, 2021; Wu, 2013). Another option that is far less understood but also important is resource idling, whereby firms halt the use of their resources temporarily to possibly reengage them in the future. There have been a few studies on this second option in general, either modeled formally (Brennan and Schwartz, 1985; McDonald and Siegel, 1985; Trigeorgis, 1996) or explored empirically (Brown, Carpenter, and Petersen, 2019; Corts, 2008; Moel and Tufano, 2002).[1] Moreover, while research on redeployment has expanded greatly in recent years, it has not accounted for the possibility that firms can respond to changing market conditions by first idling their resources. Similarly, the few studies that exist on idling have not considered the exercising of other options after reactivating those idled resources. Thus, previous research has provided researchers with a deeper understanding of determinants and effects of each option in isolation, it has not characterized how multiple options, such as resource redeployment and resource idling considered in this study, are used in conjunction with each other and potentially interact as flexible resource allocation strategies. A combined theoretical and empirical treatment of the two options therefore holds the possibility of adding new

[1] Other options that are also involved in resource allocation were reviewed in Trigeorgis (1996). Their discussion is omitted in this study to focus on precise identification of the two highlighted options that are typical of the considered empirical context.

insights into resource allocation and even potentially challenging existing insights that have been built based upon an independent treatment of each option.

The opportunity identified above provides the main purpose of this study: to investigate how the two resource allocation strategies, idling and redeployment, are used together and interact with each other. While redeployment is considered a key resource allocation strategy for the firm to alter and reconfigure its resource base (*i.e*., Folta, Helfat, & Karim, 2016; Sakhartov & Folta, 2014), idling can be another important strategy that affords the firm flexible capacity choices to temporarily alter the scale of of its operations and resources based on evolving market conditions over time (Brennan and Schwartz, 1985; McDonald and Siegel, 1985; Trigeorgis, 1996). This study is based on theory developed by adapting previous formal models of resource redeployment (Feldman and Sakhartov, 2021) to add resource idling as a means of managing resources.

The model considers a firm that can idle its resources and redeploy them to another use, after idling or without idling. The model reveals that resource idling affects the use of resource redeployment, systematically and significantly. In general, redeployment is more likely after idling than without idling. The rise in the odds of redeployment holds because, after idling was used by the firm, this alternative no longer competes with redeployment in how the firm can address adverse changes in its profit. Alternatively, if idling was not used yet, it remains an alternative to redeployment in how the firm copes with such changes, thus reducing the use of redeployment. In addition, the rise in the odds of redeployment due to the previous use of idling makes the use of redeployment more sensitive to its key determinants. The first of these known determinants is the inducement to redeploy the firm's resources to another use that provides the firm with higher returns. This inducement acts as an opportunity cost to continuing the original use (Levinthal and Wu, 2010). The second determinant is the redeployment cost that the firm incurs in withdrawing resources from the original use and putting them into another use, thus losing some efficiency in the resource use (Montgomery and Wernerfelt, 1988). In sum, the model predicts that the previous use of idling strengthens both the positive effect of the inducement and the negative effect of the redeployment cost on the use of redeployment. The fact that idling has these direct and indirect effects on resource redeployment underscores the importance of considering both resource allocation options at the same time in future theoretical and empirical research.

To test these predictions empirically, the study analyzes data collected on oil wells drilled in Texas over 25 years. In this empirical context, the resource that can be idled and/or redeployed is the rig that is owned by an oil-drilling contractor. The driller can "stack" the rig, thus temporarily idling it but holding the option to reopen it in the future; or the driller can withdraw the rig from the well in the original field and redeploy it to a well in another field. Moreover, in this empirical context, redeployment can happen without idling, when the rig is redeployed to another field after having been active in the original field. Redeployment can also occur after idling, when the rig is redeployed to another field having been stacked in the original field for some time. The use of each of these resource allocation strategies is observed directly in the data by tracking the operational status and movement of rigs. Because resource idling is a choice that can potentially affect resource redeployment, the empirical approach should account for the selection into resource idling in the first place. Therefore, the study uses a two-stage residual inclusion (2SRI) model and an accompanying regression switching model suitable for non-linear estimation predicting dichotomous outcomes.

The empirical results confirm that resource redeployment is more likely after resource idling, and that the previous use of idling reinforces both the positive effect of the inducement and the negative effect of the redeployment cost on the use of resource redeployment. Moreover, the empirical approach validates the need to consider resource idling as an important precursor to resource redeployment. Namely, the empirical evidence suggests that the positive effect of idling on the likelihood of redeployment is stronger once the endogeneity of this resource reallocation strategy is accounted for. Overall, the results confirm the predictions stemming from the formal model and demonstrate that they are economically meaningful.

The first and primary contribution of this paper is that it demonstrates how the two resource allocation strategies – idling and redeployment – are used together by firms and thus should be considered together by researchers in the future. Despite repeated calls for the joint consideration of multiple interacting options that are available to firms (Adner and Levinthal, 2004; Chi *et al*., 2019; Folta and O'Brien, 2004; Trigeorgis, 1993; Trigeorgis and Reuer, 2017; Vassolo, Anand, and Folta, 2004), resource idling and resource redeployment have always been investigated separately from each other in existing theoretical and empirical research. It might also be that the relatively limited attention to idling when considering redeployment decisions can be explained by modern resource-based perspectives in strategy that suggest idleness should be avoided (Penrose, 1959), or indicate that unused or excess resources should be redeployed or even divested (Sirmon, Hitt, and Ireland, 2007). Yet it is not necessarily inefficient to idle resources, as an argument can be made that "it is better for productive resources to remain idle for a time than to be misused" (Hutt, 1977). As existing research has focused on redeployment alone or has separately treated these options, important causal relationships in the allocation of resources have been omitted. By contrast, we theoretically and empirically demonstrate that resource idling can be an important precursor to resource redeployment, and it moderates the effects of the known determinants of redeployment on the use of redeployment.

The second contribution of this study is that it demonstrates that the omission of the derived interactions between idling and redeployment introduces biases in the estimates in the determinants of the use of resource redeployment considered in isolation. Specifically, this paper provides compelling evidence in the empirical context of oil-drilling not only for the existence of such biases but also for their economic significance, thus demonstrating the need to consider a portfolio of resource allocation options available to a firm. To illustrate the potency of the bias from disregarding the selection into idling as a possible precursor to redeployment, this study demonstrates that the effect of idling on the likelihood of redeployment is underestimated without accounting for endogeneity. In fact, this effect is over 40% higher after accounting for endogenous selection. Then, to illustrate the potency of the bias from omitting the interaction effects with idling on redeployment in this context, when redeployment is predicted from the inducement, the positive effect that the inducement has on redeployment is 59 percent stronger for idled rigs than for non-idled rigs. In turn, when redeployment is predicted from the redeployment cost in this context, the negative effect that redeployment cost has on redeployment is 41 percent stronger for idled rigs than for non-idled rigs. The next section presents a formal model of resource allocation that leads to the research hypotheses. A presentation of the empirical evidence follows. The study concludes with suggestions for the development of research on resource redeployment and the broader topic of resource allocation.

RESEARCH HYPOTHESES

Hypotheses for the context where resource redeployment and resource idling are both present are derived by extending the formal model of resource redeployment in Feldman and Sakhartov (2021) to add the possibility that such redeployment is preceded by resource idling.[2] The expanded model focuses on an oil-drilling firm that used its rig on the oil well situated in the original field. Namely, before time $t=0$, the firm deployed its rig in field i, which is denoted in the model as $m_{i0-\partial t}=1$. At any time before the end of the useful life of the rig $t=T$, the firm can idle that rig by temporarily halting its use. At any future time before $t=T$, the firm can reopen its rig and continue drilling in the original field. In addition, the firm can redeploy its rig to the alternative field j, from both the active mode where the rig was used to drill the original well in the immediate previous time and the idled mode where the rig was not used in the immediate previous time period. If idling in the original field i occurs at time t, the firm's choice as to where its rig is used switches from $m_{it-\partial t}=1$ and $m_{jt-\partial t}=0$ to $m_{it}=0$ and $m_{jt}=0$. If redeployment of the active rig to the alternative field j happens at time t, the firm's choice as to where its rig is used switches from $m_{it-\partial t}=1$ and $m_{jt-\partial t}=0$ to $m_{it}=0$ and $m_{jt}=1$. If redeployment of the idled rig to the alternative field j happens at time t, the firm's choice as to where its rig is used switches from $m_{it-\partial t}=0$ and $m_{jt-\partial t}=0$ to $m_{it}=0$ and $m_{jt}=1$. If reopening of the idled rig in the original field i happens at time t,

[2] A reverse order, in which resource redeployment precedes resource idling was also tried in the model. This alternative scenario never occurs in the dynamically optimal model of resource allocation for the following reason. The firm uses resource idling to avoid losses, only in scenarios with unfavorable realizations of revenue. When such scenarios are expected in the destination to which the firm's resources are considered to be redeployed, the firm would not use that redeployment in the first place.

the firm's choice as to where its rig is used switches from $m_{it-\partial t}=0$ and $m_{jt-\partial t}=0$ to $m_{it}=1$ and $m_{jt}=0$.

The presentation of the model involves five elements: (1) a specification of the firm's revenue in the two fields, (2) a specification of the idling option, (3) a specification of the redeployment option, (4) an account of how the firm uses these options, and (5) a summary of key results.

Revenues in two fields

Revenues that the firm can receive in the two fields are uncertain, with uncertainty represented with the following geometric Brownian motions:

$$R_{it} = R_{i0} e^{\left[\left(\mu_i - \frac{\sigma_i^2}{2}\right)t + \sigma_i W_{it}\right]} \qquad (1)$$

$$R_{jt} = R_{j0} e^{\left[\left(\mu_j - \frac{\sigma_j^2}{2}\right)t + \sigma_j W_{jt}\right]} \qquad (2)$$

$$dW_{it}\, dW_{jt} = \rho\, dt\ . \qquad (3)$$

In Equations 1–3, R_{it} and R_{jt} are current (*i.e.*, at any time t) rates of revenues the firm would receive per unit of time by using the rig in fields i and j, R_{i0} and R_{j0} are present (*i.e.*, at present time $t=0$) rates of revenues the firm would receive per unit of time by using its rig in fields i and j; μ_i and μ_j are drifts for these revenues; σ_i and σ_j are volatilities of the revenues that capture the extent of uncertainty; and W_{it} and W_{jt} are Brownian motions with correlation ρ. This specification is common in models of resource redeployment (*e.g.*, Feldman and Sakhartov, 2021; Reuer and Sakhartov, 2021; Sakhartov, 2022; Sakhartov and Folta, 2014; 2015) because it makes a plausible assumption that the two random variables, R_{it} and R_{jt}, get more difficult to predict the farther they are projected into the future and because it is convenient for the numerical completion of the model.

Idling option

If at time t the firm starts idling its rig in the original field i, it pays the idling cost proportionate to the current revenue R_{it} in the original field i; that costs represents the only cash flow (*i.e.*, the outflow) for the firm at time t. The value that the firm expects to accumulate from time t to time $t = T$ in this case is specified with the following Bellman equation (Bellman, 1957):

$$V_t^{xyA \to I} = -\alpha \gamma R_{it}^x \partial t + e^{-r\partial t} E^{P^{ij}} \left[V_{t+\partial t} \mid \left(m_{it}^* = 0, m_{jt}^* = 0 \right) \right]. \qquad (4)$$

In Equation 4, α is the proportion of the idling cost that is incurred upon idling; γ is the marginal idling cost (*i.e.*, per a unit of revenue); $E^{P^{ij}} \left[V_{t+\partial t} \mid \left(m_{it}^* = 0, m_{jt}^* = 0 \right) \right]$ is the expectation of the net present value of the firm starting at the immediate next time $\left(t + \partial t \right)$ with respect to the probability distribution P^{ij} for R_{it} and R_{jt} that is conditioned on the choice to idle the rig $\left(m_{it}^* = 0, m_{jt}^* = 0 \right)$; r is a risk-free interest rate; and x is the currents state for R_{it}.

Conversely, if at time t the firm reopens the previously idled rig in the original field i, it pays the remaining proportion $\left(1 - \alpha \right)$ of the idling cost, but it is scaled by the revenue at the time of reopening, rather than at the time of idling. The value that the firm expects to accumulate from time t to time $t = T$ in this case is represented with the following Bellman equation:

$$V_t^{xyI \to A} = \left(1 - \alpha \right) \gamma R_{it}^x \partial t + \left(R_{it}^x - C_i \right) \partial t + e^{-r\partial t} E^{P^{ij}} \left[V_{t+\partial t} \mid \left(m_{it}^* = 1, m_{jt}^* = 0 \right) \right]. \qquad (5)$$

In Equation 5, C_i is the time-invariant rate of costs the firm would incur per unit of time by drilling in fields i; $E^{P^{ij}} \left[V_{t+\partial t} \mid \left(m_{it}^* = 1, m_{jt}^* = 0 \right) \right]$ is the expectation for the immediate next value of the firm conditioned on the current choice to reopen the rig $\left(m_{it}^* = 1, m_{jt}^* = 0 \right)$.

If at time t the previously idled rig continues to be idled, the value that the firm expects to create from time t to time $t = T$ in this case is specified with the following Bellman equation:

$$V_t^{xyI} = 0 + e^{-r\partial t} E^{P^{ij}} \left[V_{t+\partial t} \mid \left(m_{it}^* = 0, m_{jt}^* = 0 \right) \right]. \quad (6)$$

Redeployment option

If the firm redeploys its active rig to the alternative field j, the rate of revenue the firm earns with the rig that is withdrawn from the original field i is lower than the regular rate of revenue R_{jt} in field j, by S_t^y, the rate of the redeployment cost. This rate of the redeployment cost the firm would incur per unit of time is a product of the marginal redeployment cost s and the current realization R_{jt}^y of the rate of revenue R_{jt} on the destination field when that random variable is in state y, thus showing the loss in the rate of revenue due to redeployment. Formally,

$$S_t^y = \mathbf{1}_{\left(m_{jt}=1, m_{it-\partial t}=1 \right)} sR_{jt}^y. \quad (7)$$

Term $\mathbf{1}_{\left(m_{jt}=1, m_{it-\partial t}=1 \right)}$ in Equation7 is a dummy that is equal one only when the rig transitions from being actively used in field i at the immediate previous time $\left(t - \partial t \right)$ to being actively used in field j at the current time t. Equation 7 leads to the following statement of the expected net present value $V_t^{yA\to R}$ of the firm that redeploys the active rig to field j at time t:

$$V_t^{yA\to R} = \left(-S_t^y + R_{jt}^y - C_j \right) \partial t + e^{-r\partial t} E^{P^j} \left[V_{t+\partial t}^y \mid \left(m_{it}^* = 0, m_{jt}^* = 1 \right) \right]. \quad (8)$$

In Bellman Equation 8, C_j is the time-invariant rate of costs the firm would incur per unit of time by drilling in fields j; and $E^{P^j} \left[V_{t+\partial t}^y \mid \left(m_{it}^* = 0, m_{jt}^* = 1 \right) \right]$ is the expectation with respect to the probability distribution P^j that the random variable R_{jt} follows conditioned on the current choice to redeploy the rig. This expectation is assessed when revenue R_{jt} is in state y.

If the firm redeploys its idled rig, Equations 7 still holds for S_t^y, but the dummy term changes to $\mathbf{1}_{\left(m_{jt}=1, m_{it-\partial t}=0, m_{jt-\partial t}=0 \right)}$ (*i.e.*, the rig was idled at time $\left(t - \partial t \right)$ and is redeployed to field j at the current time

t). Then, the following Bellman equation summarizes the expected net present value $V_t^{yI\to R}$ of the firm that redeploys the idled rig to field j at time t:

$$V_t^{yI\to R} = \left(-S_t^y + R_{jt}^y - C_j\right)\partial t + e^{-r\partial t} E^{P^j}\left[V_{t+\partial t}^y \mid \left(m_{it}^* = 0, m_{jt}^* = 1\right)\right] \qquad (9)$$

If the rig was already redeployed to field j before time t, the following Bellman equation holds because no redeployment cost is incurred at the current time t:

$$V_t^{yR} = \left(R_{jt}^y - C_j\right)\partial t + e^{-r\partial t} E^{P^j}\left[V_{t+\partial t}^y \mid \left(m_{it}^* = 0, m_{jt}^* = 1\right)\right]. \qquad (10)$$

Finally, if at time t the rig continues to be active in field i (*i.e.*, neither idled nor redeployed), the following Bellman equation holds for the net present value of the firm:

$$V_t^{xyA} = \left(R_{it}^x - C_i\right)\partial t + e^{-r\partial t} E^{P^{ij}}\left[V_{t+\partial t} \mid \left(m_{it}^* = 1, m_{jt}^* = 0\right)\right]. \qquad (11)$$

Use of resource allocation options

Resource idling and resource redeployment are options, rather than obligations, for the firm. Each option is exercised by the firm only if doing so makes the firm better off. Formally,

$$V_t^{xy} = \left[\begin{array}{ll} \max\left[\begin{array}{l} V_t^{xyA} \\ V_t^{xyA\to I} \\ V_t^{yA\to R} \end{array}\right. & \text{if} \quad m_{it-\partial t} = 1,\ m_{jt-\partial t} = 0 \\ \max\left[\begin{array}{l} V_t^{xyI} \\ V_t^{xyI\to A} \\ V_t^{yI\to R} \end{array}\right. & \text{if} \quad m_{it-\partial t} = 0,\ m_{jt-\partial t} = 0 \\ V_t^{yR} & \text{if} \quad m_{it-\partial t} = 0,\ m_{jt-\partial t} = 1 \end{array}\right. . \qquad (12)$$

In Equation 12, the first three lines represent the situation where the firm enters time t with the rig having been actively used to drill the well in field i. Accordingly, the firm chooses among continuing to drill the well in field i and the respective value V_t^{xyA} (*i.e.*, Equation 11), starting to idle the rig in field i and the respective value $V_t^{xyA\to I}$ (*i.e.*, Equation 4), and redeploying its rig to the alternative field j and the respective value $V_t^{yA \to R}$ (*i.e.*, Equation 8). In this setting, idling (*i.e.*, $A \to I$ in V_t) competes with, or reduces the use of, redeployment (*i.e.*, $A \to R$ in V_t) as a means for the firm to respond to adverse changes in revenue R_{it} in the original field because both options are more likely to be "in the money" when R_{it} is low.

The second three lines in Equation 12 capture the situation where the firm enters time t with the rig having been idled in field i. Accordingly, the firm chooses among continuing to idle the rig in field i and the respective value V_t^{xyI} (*i.e.*, Equation 6), reopening the rig in the original field i and the respective value $V_t^{xyI \to A}$ (*i.e.*, Equation 5), and redeploying its rig to the alternative field j and the respective value $V_t^{yI \to R}$ (*i.e.*, Equation 9). In this context, the firm cannot start idling the rig that was idled already; and reopening (*i.e.*, $I \to A$ in V_t) does not compete with redeployment (*i.e.*, $I \to R$ in V_t) because they diverge in the conditions that make them in the money: the former is in the money with favorable changes in R_{it}, whereas the latter is still more likely to be in the money when R_{it} becomes low. Accordingly, that choice of redeployment after idling that is less contested by the alternative option than the choice of redeployment without idling should lead to a higher intensity of redeployment.

Equation 12 can be restated with respect to the current resource allocation choices $m_{it}^* \in \{0,1\}$ and $m_{jt}^* \in \{0,1\}$ in the following way:

$$\left[\left(m_{it}^*, m_{jt}^*\right) \middle| \left(m_{it-\partial t}, m_{jt-\partial t}\right)\right] = \begin{bmatrix} \arg\max\limits_{(m_{it}, m_{jt})} \begin{bmatrix} V_t^{xyA} \\ V_t^{xyA \to I} \\ V_t^{yA \to R} \end{bmatrix} & \text{if} \quad m_{it-\partial t} = 1,\ m_{jt-\partial t} = 0 \\ \arg\max\limits_{(m_{it}, m_{jt})} \begin{bmatrix} V_t^{xyI} \\ V_t^{xyI \to A} \\ V_t^{xyI \to R} \end{bmatrix} & \text{if} \quad m_{it-\partial t} = 0,\ m_{jt-\partial t} = 0 \\ (0,1) & \text{if} \quad m_{it-\partial t} = 0,\ m_{jt-\partial t} = 1 \end{bmatrix}. \qquad (13)$$

Because Equations 4-6 and 8-11 are Bellman equations that capture dynamic implications of the current choice $\left(m_{it}^{*}, m_{jt}^{*}\right)$ (*i.e.*, how that choice affects not only the current cash flow represented with the first term in each of these equations but also the future cash flows captured with the second term in each of these equations), Equations 12 and 13 are also Bellman equations that cast the firm's resource allocation choice $\left(m_{it}^{*}, m_{jt}^{*}\right)$ as dynamically optimal. The Bellman equations split the problem of resource allocation into a sequence of sub-problems that are amenable to a numerical solution. Such dynamically-optimal resource allocation choices are expressed in a recursive form that relies on backward induction to derive optimal conditional choices $\left[\left(m_{it}^{*}, m_{jt}^{*}\right)\middle|\left(m_{it-\partial t}, m_{jt-\partial t}\right)\right]$ at all times t and with all values of R_{it}^{x}, and R_{jt}^{y}. The solution uses the discretization of the continuous-time distribution P^{ij} specified with Equations 1–3. Like Feldman and Sakhartov (2021), this model applies the popular and efficient discretization suggested by Boyle, Evnine, and Gibbs (1989) that approximates geometric Brownian motions with a binomial lattice having N time steps. This approach preserves the mean and the variance of the original distribution if the time step $\partial t = T/N$ on the lattice is sufficiently short. On the lattice, the next-period revenues $R_{it+\partial t}$ and $R_{jt+\partial t}$ represent four nodes and take four respective states: $R_{it+\partial t}^{u}$ and $R_{jt+\partial t}^{u}$ with probability q^{uu}, $R_{it+\partial t}^{u}$ and $R_{jt+\partial t}^{d}$ with probability q^{ud}; $R_{it+\partial t}^{d}$ and $R_{jt+\partial t}^{u}$ with probability q^{du}; or $R_{it+\partial t}^{d}$ and $R_{jt+\partial t}^{d}$ with probability q^{dd}.[3] The expectations in Equations 4-6 and 8-11 are estimated as $E\left[V_{t+\partial t}^{xy}\right] = q^{uu}V_{t+\partial t}^{uu} + q^{ud}V_{t+\partial t}^{ud} + q^{du}V_{t+\partial t}^{du} + q^{dd}V_{t+\partial t}^{dd}$.

The backward induction procedure starts at the penultimate time $t = T - \partial t$ with the terminal condition $V_{T}^{xy} = 0$ suggesting that the rig will have fully exhausted its ability to generate revenues by terminal time T. The algorithm proceeds recursively backward in time with a step ∂t until it reaches the

[3] Formulas for $R_{it+\partial t}^{u}$, $R_{jt+\partial t}^{u}$, $R_{it+\partial t}^{d}$, $R_{jt+\partial t}^{d}$, q^{uu}, q^{ud}, q^{du}, and q^{dd} are given in Feldman and Sakhartov (2021).

present time $t = 0$. In each step going backward in time and for each combination of revenues R_{it}^{x} and R_{jt}^{y}, the model derives conditional choices $\left[\left(m_{it}^{*}, m_{jt}^{*}\right) \middle| \left(m_{it-\partial t}, m_{jt-\partial t}\right)\right]$. One type of such choices, $\left[\left(m_{it}^{*}=0, m_{jt}^{*}=1\right) \middle| \left(m_{it-\partial t}=1, m_{jt-\partial t}=0\right)\right]$, represents redeployment of the rig conditioned on that rig having been active in the original field in the immediate previous time. Another type, $\left[\left(m_{it}^{*}=0, m_{jt}^{*}=1\right) \middle| \left(m_{it-\partial t}=0, m_{jt-\partial t}=0\right)\right]$, represents redeployment of the rig conditioned on that rig having been idle in the original field in the immediate previous time. Finally, the resulting three-dimensional matrix (*i.e.*, with t, x, and y being the three dimensions) generated for the two choices enables the following analyses.

Formal results

The formal results predict the probability of resource redeployment that is conditioned on *either* previous idling *or* previous non-idling. Each of these results involves two determinants of resource redeployment. The first determinant is the inducement to redeploy the rig from the original field to another field, namely whether and to what extent the revenue on the drilling contract would be higher in another field than in the original field. The second determinant is the redeployment cost the firm would incur when withdrawing the rig from the original field and reallocating it to another field. Accordingly, the formal results are visualized in two figures and are summarized with three hypotheses concluding this section.

Figure 1 displays the effects the inducement has on the use of resource redeployment conditioned on the previous idling of the resources (*i.e.*, the broken line) and on the previous non-idling of the resources (*i.e.*, the solid line). The vertical axis reflects the probability of resource redeployment that is averaged over time, the redeployment cost, and the idling cost in the model.[4] The horizontal axis spans

[4] The estimation uses the following ranges for the three parameters, over which the estimated probabilities are averaged: $t \in [0,\ 1]$, $s \in [0, 100]$, and $\gamma \in [0,\ 10]$. The inducement varies within the range $\left(R_{j0} - R_{i0}\right) / R_{i0} \in [-90\%, 90\%]$, which is

values of the inducement. The following three results in Figure 1 are noteworthy. First, the broken line is above the solid line. This result suggests that the probability of resource redeployment is greater after idling than without idling. This monotonic positive effect of resource idling on resource redeployment occurs for the following reason. After idling was already undertaken by the firm, it no longer competes with redeployment as a means of addressing low revenue in the original field. By contrast, if idling was not used, it competes with redeployment to address low revenue in the original field, thus reducing the use of resource redeployment. Second, both the solid and the broken lines have robust upward slopes. This result suggests that the probability of resource redeployment monotonically increases in the inducement, thus validating that the model is consistent with the effect expected for this determinant. Third, the elevation of the broken line over the solid line increases monotonically in the direction from the left margin to the right margin in Figure 1. This result suggests that the magnitude of the diagnosed positive effect of the inducement on the use of resource redeployment increases after the resources were idled. This positive moderation takes place because, with the revealed higher intensity of resource redeployment after idling, resource redeployment becomes more sensitive to its key determinant—the inducement.

[Insert Figure 1 about here]

Figure 2 illustrates the effects of the redeployment cost on the use of resource redeployment conditioned on the previous idling of the firm's resources (*i.e.*, the broken line) and on the previous non-idling of those resources (*i.e.*, the solid line). The vertical axis reflects the probability of resource redeployment that is averaged over time, the inducement, and the idling cost.[5] The horizontal axis spans values of the redeployment cost. The first observation in Figure 2 is that, like in Figure 1, the broken line

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provided by fixing $R_{i0} = 0.08$ and setting the range for $R_{j0} \in [0.008, 0.152]$. Other ancillary parameters in the model take the following values: $\alpha = 0.25$, $\sigma_i = \sigma_j = 0.5$, $\rho = 0$, $C_i = C_j = 0.07$, $r = 0.08$, $T = 1$, and $N = 200$.

[5] The estimation uses the following ranges for the three parameters, over which the estimated probabilities are averaged: $t \in [0,\ 1]$, $R_{j0} \in [0.008, 0.152]$, and $\gamma \in [0,\ 10]$. The redeployment cost varies within the range $s \in [0, 100]$. Other ancillary parameters are as follows: $\alpha = 0.25$, $R_{i0} = 0.08$, $\sigma_i = \sigma_j = 0.5$, $\rho = 0$, $C_i = C_j = 0.07$, $r = 0.08$, $T = 1$, and $N = 200$.

stays above the solid line. This result validates the conclusion that previous idling of the firm's resources increases the use of resource redeployment. The second noteworthy pattern is that both the solid and the broken lines have robust downward slopes. This result suggests that the probability of resource redeployment monotonically declines in the redeployment cost, thus confirming that the model is consistent with the effect expected for this determinant of resource redeployment. Finally, the elevation of the broken line over the solid line declines monotonically in the direction from the left margin to the right margin in Figure 2. This result indicates that the negative effect of the redeployment cost on the use of resource redeployment becomes stronger after the resources were idled. The negative moderation occurs because, with the higher intensity of redeployment after idling, resource redeployment becomes more sensitive to its key determinant—the redeployment cost.

[Insert Figure 2 about here]

The three novel results that are demonstrated in Figures 1 and 2 can be restated as the following three hypotheses, which are then tested empirically.

Hypothesis 1: Resource idling has a positive effect on resource redeployment.

Hypothesis 2: The positive effect of the inducement on resource redeployment will be greater for idled resources than non-idled resources.

Hypothesis 3: The negative effect of the redeployment cost on resource redeployment will be greater for idled resources than non-idled resources.

METHODS

Empirical context: Oil drilling industry

To empirically examine study resource idling and resource redeployment, this study investigates idling and redeployment of drilling rigs in the onshore oil drilling industry. As background information, oil reserves are discovered in different geologic formations underground, and the goal of a production company owning the site where these reserves are present is to pump the oil from them to process and sell it. To achieve this, the producer first contracts with a driller to use its rig, which is a tall derrick run by a motor that spins a pipe attached to a drill bit, to crush through layers of rock sediments to reach the pockets of oil and gas reserves deep underground. The industry is vertically disintegrated due to the spatial and temporal variation with which producers develop wells (Corts and Singh, 2004). Drilling activities fluctuate with the producers successfully finding new fields with oil and with oil prices; and the non-specificity of equipment and mobility demanded of rigs favors independent drillers, where their rigs are more effective in smoothing out these fluctuations in drilling requirements across different producers (Kellogg, 2011). Every oil field can be considered a distinct market from another field because the opportunity set can vary depending on how many undrilled wells are available, who the client producers are operating there, and what the geological terrain is like to drill (Decaire, Gilje, and Taillard, 2020; Kellogg, 2011, 2014).

This industry is well suited to empirically study resource idling and redeployment for several reasons. First, idling rigs is critical for a driller to maintain flexible capacity in response to volatile market conditions in the oil industry (Corts, 2008). This empirical context therefore allows this study to observe whether rigs are idled. Second, resource redeployment is a critical strategy used by drillers to optimize opportunities for their rigs. Drillers are actively looking for new opportunities for their rigs to be put to work, and their rigs are often redeployed from previously completed wells to locate next to new wells that are opening up for development. By having its rig physically closer to an available well, the driller makes itself more attractive to its potential client by minimizing the setup cost and time to commence drilling operations compared to other drillers with rigs located further away (Chowdhury, 2016). This empirical context allows us to observe whether rigs are redeployed by geospatially tracking their movements, especially across oil fields (from a well in its home field to a new well located in an outside field). Finally, the important determinants for resource redeployment according to the literature—the inducement and the redeployment cost—are key considerations for drillers in making such decisions, and this empirical context captures these factors well (Chowdhury, 2016).

Data and sample

Our data are collected from the Texas Railroad Commission (TRC), DrillingInfo, RigData, and the Energy Information Administration (EIA). TRC is the state regulatory agency that overseas all oil and gas drilling in Texas and records well-level activities. DrillingInfo and RigData are private data providers for the oil and gas industry that track drillers, producers, and their activities. EIA the federal agency that provides macro-level economic data on the industry. By combining these data sources, we construct a unique dataset that allows us to observe characteristics of the drillers, their rigs, their client producers, and the revenue prospects of project sites. More importantly, we can observe detailed activities of drillers' rigs, enabling us to determine whether and when they idle their operations, to track their geospatial movements when they are redeployed between project sites and markets, and to determine far they travel if they have been redeployed. Our sample period is between the years 1991 and 2015.

The decision problem, resource redeployment, requires structuring the data in the following way. A driller's rig enters the sample when that rig becomes available for possible redeployment. Specifically, a rig is observed for every well drilled during our observation period, and after a given well's completion, the driller faces a key decision problem: whether to redeploy to an outside market (or new field) by transporting that rig there for work, or to stay in its home market (or home field) by using that rig on a project nearby. The driller's redeployment targets can be any new well located in these outside markets that need to be developed at that time. In other words, a driller faces the choice set of potential redeployment dyads for its rig, as represented by the original well and all potential redeployment target wells. Thus, we structure our data by compiling a set of realized and unrealized dyads between a focal rig located at its original well in its home field and every potential new well in alternative outside fields. For an available rig, the driller faces another important strategic choice prior to its redeployment decision: idling that rig or keeping it online to be fully ready when the next project calls. Based on our theorizing and empirical design, we lag this key predictor and our other explanatory variables, which precede the redeployment decision by one month. Creating this naturally lagged temporal structure also helps with identification and mitigates endogeneity concerns (elaborated below in the section entitled "Analytical approach").

Following this empirical setup, the final sample used in analyses comprises 1,005,901 total observations, which are potential idling and redeployment decisions every month over the 25 years in the sample. In this choice set during the sample period, 63,204 observations are realized dyads in terms of instances of redeployment, and the remaining 942,695 observations are unrealized dyads that are associated with 3,353 rigs that are owned by 268 drillers that operate purely in the drilling business. In the sample, 66% of drillers idle at least one rig in their fleet in a given year. Among these drillers that have idled, 52% redeploy at least one rig in their fleet in the same year, while the rest that have idled rig did not redeploy any rig. Drillers that did not idle in a given year represented on average 34% of all drillers in the sample. Among these non-idled drillers, about 26% redeployed at least one rig in their fleet, while the rest did not redeploy any rigs. These patterns overall suggest that idling is an option that the majority of drillers exercise in a given year, and among those idling their rigs many redeploy some of those rigs to an outside market.

Variables

Dependent variable

The dependent variable *Redeployed* is a binary measure of whether the drilling rig is moved from the oil well in its original home field to a target well in a different oil field (=1), or stays in its home field (=0). As explained above, the focal rig's redeployment choice set of potential target wells includes all available wells located outside its original home field.

Explanatory variables

The first explanatory variable *Idled* is measured as a binary indictor of whether the driller idles a given rig. A driller's rig becomes idled, or what is termed "stacked" in the drilling industry, when its drilling operations are suspended and its assigned crew members are furloughed. In the extreme case, idling a rig entails complete deactivation by disassembling it and placing it into storage, and laying off its crew members. A driller can then reactivate its "stacked" rig, which often requires retraining furloughed workers or rehiring after layoffs. The reactivation also requires additional investment to refurbish the rig due to any physical erosion and even reassemble parts or the entire rig.

The second explanatory variable is *Inducement*, which captures the relative financial advantage of the firm's potential target market relative to its home market. We measure this variable for each dyad associated with the rig's original well site in its home field and the potential target well site in an outside field. Specifically, the payment to the driller on the current well is calculated as the price per foot paid to the contractor in drilling that well (in hundreds of dollars). Because we cannot observe the actual payment for a new well that has not been drilled yet, the expected payment for each potential target well site is calculated as the average price per foot drilled paid to drillers for recently-completed nearby wells in the same field during the same year as the target well becoming available (in hundreds of dollars). Finally, we estimate inducement for each dyad by taking the difference between the potential payment of the target well site for redeployment and the payment the contractor received for its rig used on the current well site.

The third explanatory variable is *Redeployment cost*, which is the cost for the firm to switch from its home market to a new market. This variable is measured as the geographical distance (in miles) between the site of the rig's current well in its home field and the site of the potential well in an outside field. A rig traveling a longer distance requires higher transportation cost. For instance, based on 2011 rig mobilization data, the trucking fee for transporting a standard drilling rig was about $130,000 for every 25 miles. Moves for more than 50 miles are often considered long hual moves and typically involve even higher mileage rates (Carpenter, 2019).

Control variables

We included the following control variables to account for other determinant of redeployment. First, the technical complexity of the project can influence redeployment decisions. More technically-complex wells pose greater challenges to effectively drill and entail greater risks of accidents occurring. Considering a target well that is more complex, all else equal the driller is more likely to seek more manageable projects elsewhere. At the same time, a driller that has worked on technically-complex well in its home market may seek to leverage that experience for its new wells. We thus control for both *Focal well complexity* and *Target well complexity*, which we each measure by assigning "0" to a standard vertical well, "1" to a directional well that requires non-vertical and diagonal drilling that is more technically complex, and "2" to a horizontal well that requires the most complex drilling maneuver in drilling.

Also, the experience level of the firm and its frontline team can affect redeployment decisions. A driller's rig, and its associated crew, with greater experience in a given field have better knowledge of the geological terrain, such as familiarity drilling through the different rock stratifications. In fact, these crew members working on a rig usually stay with that rig given the significant rig-specific knowledge and training involved. As a result, a rig with more experience in its home field operates more efficiently, such as achieving faster completion times while incurring lower costs, and is thus less likely to be redeployed elsewhere. Accordingly, we control for *Rig field experience* by measuring this variable as the number of previous wells drilled and completed in the rig's current field.

Resources are more likely to be redeployed to a new market when they underperform in the home market. The primary metric with which drillers are evaluated in the industry is the drilling speed of its rigs in terms of how fast they can complete drilling operations on wells (Kellogg, 2011). We control for *Rig performance*, which is measured following past literature as a rig's drilling speed is measured as feet drilled per day. When under contract, rigs operate continuously, working 24 hours per day and 7 days per week, rotating crews in three 8-hour shifts. Specifically, a rig's performance for a given well is calculated by taking the total depth of a given well and then dividing it by the total number of drilling days needed to complete the well.[6]

[6] However, there could be systematic differences at the project level that can impact a driller's drilling speed, such as differences in the wells' characteristics and environmental factor. This means that the realized drilling speed of the well needs to be decomposed into the factors intrinsic to the rig and external determinants of such speed. The rig's intrinsic speed is assessed using the approach common in the literature (Hawk, Pacheco-De-Almeida, and Yeung, 2013; Pacheco-de-Almeida, Hawk, and Yeung, 2015). Namely, the rig's observed drilling speed is regressed on a set of project-level factors, and then he residual from that regression embodies the remaining rig-specific, idiosyncratic component of the rig's drilling speed. Specifically, in the first stage, the following OLS model is run using the drilling data at the project well level (indexed for well, field, and time): a rig's drilling speed for a given well is regressed on project-level factors. In this regression, the outcome of drilling speed is measured as the feet per day drilling rate achieved for the well. The explanatory variables proxying for the systematic determinants are the type of well (vertical, directional, or horizontal); the cost of the well in thousands of US dollars; the contract type being either day rate or turn key; the demand conditions at the time of the drilling based on oil consumption data from the U.S. Energy Information Administration (EIA) in millions of barrels; and a vector of dummies capturing fixed effects for each field (based on geography of the drilling), product type (types of crude oil produced), and year. If the residual in that estimation is positive, it captures the degree to which the rig realizes a faster than expected drilling rate for the given well. If the residual is negative, it

Another important performance consideration for redeployment is how profitable the focal asset is in its home market. A rig that has been more profitable at home has less incentives to leave for a new market. We thus control for *Rig profitability*, which is measured as the average profit made for its previously drilled wells in its home field in the past year based on the average revenue earned on those wells minus the average cost in drilling those wells.

The intensity of competition that the firm faces in its home market and target markets can also affect redeployment decisions. A driller's rig facing more competitition in its home market can lead it to pursue opportunities in other, less competitive locations; whereas a rig facing more competiton in a target market can redeployment there less appealing. Thus, we control for *Focal competitive density*, which is measured based on the number of rival drillers operating in the same home field as the focal rig. Likewise, we control for *Target competitive density*, which is measured in a similar way by counting the number of rival rigs operating in the same field as the target well site.

Finally, we control for *Uncertainty* to capture the degree of unpredictability of revenue generated in the potential market for redeployment. We seek to estimate the extent that the realized revenue on a target well diverges from the level that would be rationally expected based on available historical information. We follow the statistical modeling technique using the conditional variance generated from generalized autoregressive conditional heteroskedasticity (GARCH model) to predict uncertainty of asset returns (Bollerslev, 1986; Greene, 2003).[7]

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captures the degree to which the rig realizes slower than expected drilling rate for the given well. This residual, then, becomes the basis for the measurement of the rig's intrinsic speed performance.

[7] In particular, we generates time series data for each target well's return over the sample period by estimating the expected revenue for each potential target well in each month, which we derive using the total feet drilled of nearby wells in the same field as the target well multiplied by the crude oil price in that period. Using the time series of a target well's expected revenue as the outcome, a GARCH model is run on an autoregressive-moving average process of past variances and disturbances of that well. This procedure is done by first regressing the target well's expected revenue on that well's expected revenue lagged by one month. Then, the conditional variance of the error term is regressed on the first-order lag of the variance itself and the squared error term, while controlling for heteroskedasticity in this time series. The estimated conditional variance captures the uncertainty that is not predictable about any trend that might exist for each period in the time series. Finally, a series of fixed effects for rig and year is added to account for differences across time and rigs.

Baseline statistical method

The analysis needs to accommodate prospective target well sites in outside fields, regardless of whether the driller redeployed a rig to a particular site because the driller can redeploy a rig from the current well to many others, or not redeploy it at all. Accordingly, dyadic measures for the explanatory variables are created for all possible pairs, thus enabling the comparisons that drive the chosen redeployment or the lack of thereof. The primary relationship between a focal rig being idled and its likelihood of redeployment can be expressed in the following Conditional Probit model:

$$Redeployed_{k,t+1} = \beta_1 Idled_{k,t} + \boldsymbol{\delta}'\boldsymbol{X}_{k,t} + \varepsilon_{k,t} \,. \tag{14}$$

When the moderating effects are examined, the model becomes as follows:

$$\begin{aligned} Redeployed_{k,t+1} &= \beta_1 Idled_{k,t} + \beta_2 Idled_{k,t} * Inducement_{k,t} \\ &+ \beta_3 Idled_{k,t} * Redeployment\ cost_{k,t} + \boldsymbol{\delta}'\boldsymbol{X}_{k,t} + \varepsilon_{k,t} \end{aligned}, \tag{15}$$

where *Redeployed* is operationalized as described above and measured at time $t+1$, the main predictor is whether the focal rig k is *Idled* at time t, the moderators are *Inducement* and *Redeployment cost*, $\boldsymbol{X}$ is a vector of control variables accounting for other determinants of redeployment that also includes rig and year fixed effects, and ε is the residual error term. The empirical specification above is potentially problematic because instances of redeployment can be influenced by endogenous choices of idling made by the firm. Showing first the baseline estimation that does not account for self-selection of operating mode can highlight how the estimations of β_1, β_2, and β_3 change after accounting for such endogeneity.

Identification strategies

The empirical objective is to estimate the effect of the decision to idle a rig on the subsequent likelihood of its redeployment. This goal requires an analytic strategy that resolves several challenges such as omitted variable bias, selection effects, simultaneity, and reverse causality. Accordingly, several identification strategies are used to cope with these empirical challenges.

The first identification strategy is *via* regression analyses, where the goal is to obtain a consistent estimate of idling on redeployment by controlling for all other potential factors that influence redeployment in a vector of control variables. The use of a fuller set of control variables mitigates omitted variable bias, thus providing a consistent estimate. To estimate the likelihood of redeployment when there are multiple alternative choices, a conditional logit model is used (McFadden, 1973). The explanatory variables also have a lagged temporal structure relative to the decision to redeploy, which reduces concerns regarding simultaneity and/or reverse causality. Specifically, the construction of variables of *Idled*, *Inducement*, and *Redeployment costs* are based on data observed at least one month before the considered redeployment decision. This temporal structure alleviates the concern that one redeployment decision of a rig could influence the values of the main explanatory variables. Also, fixed effects associated with rig and year minimize omitted variable bias concerns. Including rig-fixed effects accounts for any time-invariant rig characteristics that may affect both a rig's idling and its redeployment. Including year-fixed effects accounts for economy-wide factors that could affect both a rig's idling and its redeployment.

A potential estimation problem in testing Hypothesis 1 is that the decision to idle is likely to be influenced by unobserved factors, which creates unobserved interdependency between the decision to idle and redeployment. In general, firms can choose a strategy (*i.e*., idling or not) based on their beliefs that such a strategy leads to the best outcome (*i.e.*, related to redeployment). Thus, when firms choose strategies, regressing an outcome of that choice on that strategy choice dummy can bias estimations. If such endogeneity exists and is not accounted for, the baseline Probit regression model will generate biased estimates. Furthermore, when the effect of the endogenous variable (*i.e*., *Idled*) is not correctly adjusted, the estimation of its interaction effects (with the inducement and the redeployment cost) is also biased. To address these concerns, the analysis starts with a two-stage residual inclusion (2SRI) estimation model, which is a particularly suitable approach for addressing endogeneity bias in non-linear models involving dichotomous outcome variables (Rivers and Vuong, 1988; Terza *et al*., 2008). The 2SRI relies on a maximum likelihood (ML) estimator to accommodate the nonlinearity in the dependent variable and the endogeneity of the regressor, which helps mitigate specification error (Nakamura and Nakamura, 1998, Wooldridge, 2014). In particular, the 2SRI derives the residual in the first-stage ML estimation of the endogenous regressor and includes those estimated residuals in the second stage conditional ML estimation of the main outcome of interest (Newey, 1987; Rivers and Vuong, 1988; Blundell and Powell, 2004; Terza *et al*. 2008). The inclusion of the residual from the first stage substitutes for unobservable confounds, thus correcting for endogeneity of the regressor (Terza *et al*. 2008, Wooldridge 2014). The first stage uses relevant covariates to predict idling with a Probit model:

$$\begin{aligned} Idled^*_{k,t} &= \boldsymbol{\gamma}'\boldsymbol{W}_{k,t} + \mu_{k,t-1} \\ Idled_{k,t} &= 1 \quad \text{if} \quad Idled^*_{k,t} > 0, \quad 0 \text{ otherwise} \end{aligned} \tag{16}$$

The outcome $Idled^*_{k,t}$ is a latent measure of idling, where $Idled^*_{k,t} = 1$ corresponds to the focal rig k being idled at time t and $Idled^*_{k,t} = 0$ corresponds to the focal rig not being idled at that time. The choice variable of $Idled^*_{k,t}$ can be thought of as the difference in the expected value of idling and the expected value of remaining active at time t. This value, and therefore this chosen operational mode, is a function of measurable firm attributes and industry conditions that are included in the vector $\boldsymbol{W}_{k,t}$. Because $Idled^*_{k,t}$ cannot be observed but the chosen operational mode can (*i.e*., $Idled_{k,t} = 1$ if the focal rig is idled or $Idled_{k,t} = 0$ if focal rig remains active), the model diagnoses whether or not $Idled^*_{k,t}$ is positive or negative based on the choice of idling. Vector $\boldsymbol{W}_{k,t}$ involves independent covariates at time t that affect the decision to idle at that time, including an instrument. Vector $\boldsymbol{\gamma}$ consists of coefficients associated with those covariates. The instrument included in $\boldsymbol{W}_{k,t}$ is *Rivals cold stacking*, which likely raises the attractiveness of idling to the focal driller because such cold stacking by rivals reduces the prospective cost for the focal rig to be reactivated. Specifically, the cold stacking of rigs by rivals is the most extreme form of idling, which involves dissembling these rigs, placing them in storage, and laying off the associated crew members. Such layoffs, however, increase the available local labor market supply for rig workers, which can benefit a driller reactivating any idled rigs because it can more easily rehire needed crew members. Meanwhile, rivals cold stacking rigs is less likely to directly affect redeployment of the focal rig, thus satisfying the exclusion restriction of an instrument. Consistent with a Probit specification, the error term $\mu_{k,t-1}$ is assumed to be normally distributed with zero mean. Moreover, $\mu_{k,t-1}$ captures the effects on the outcome of idling choice that cannot be identified or measured in covariates $\boldsymbol{W}_{k,t}$. Then, the second stage is set up similar to Equation 14 but includes correction for self-selection λ that represents the treatment effect model (Greene, 2003):

$$Redeployed_{k,t+1} = \beta_1 Idled_{k,t} + \boldsymbol{\beta}_2 \boldsymbol{X}_{k,t} + \beta_3 \lambda + \varepsilon_{k,t} . \tag{17}$$

Finally, how idling moderates the effects of the inducement and of the redeployment cost on redeployment is tested. The challenge is that directly interacting the endogenous variable *Idled* based on Equation 17, even after instrumenting, can still result in biased estimation (Bun and Harrison, 2018). The analysis follows the approach of correcting for such self-selection or treatment effects using a switching regression model, which separately estimates the likelihood of redeployment for idled rigs in one sample and for non-idled rigs in another sample (Hamilton and Nickerson, 2003; Shaver, 1998). The advantage of using this switching regression model over the more commonly used treatment model that uses the full sample is that the latter approach restricts coefficient estimates for the covariates (*i.e.*, *Inducement* and *Redeployment cost*) to be the same for both operational modes (*i.e.*, idled and non-idled) and thereby does not allow comparisons of the effects between these two operational modes (Shaver, 1998).

The switching regression model also has two stages. The first stage uses relevant covariates to predict resource idling with a Probit model, which is the same as the first-stage instrumental estimation in Equation 16. In the second stage, the likelihoods of redeployment for idled rigs and non-idled rigs are estimated separately using different subsamples and including a correction for self-selection for each sample. These switching models are expressed as follows:

$$\mathrm{E}\left[Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 0 \right] = \boldsymbol{\beta}_0' \boldsymbol{X}_{k,t} + \mathrm{E}\left[\varepsilon_{k,t} \middle| Idled_{k,t} = 0 \right] \tag{18}$$

$$\mathrm{E}\left[Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 1 \right] = \boldsymbol{\beta}_0^{'} \boldsymbol{X}_{k,t} + \mathrm{E}\left[\varepsilon_{k,t} \middle| Idled_{k,t} = 1 \right]. \tag{19}$$

The outcomes of $\left(Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 0 \right)$ and $\left(Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 1 \right)$ measure whether redeployment occurs for rigs that were previously, non-idled and idled, respectively; $\boldsymbol{X}_{k,t}$ is the reduced-form vector of exogenous covariates with $\boldsymbol{\beta}_0$ being the associated vector of coefficients for the given sample. Assuming that these outcome variables are jointly distributed, the above equations 18 and 19 can be expressed as follows:

$$\mathrm{E}\left[Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 0 \right] = \boldsymbol{\beta}_0^{'} \boldsymbol{X}_{k,t} + \sigma_0 \frac{\phi\left(\boldsymbol{\gamma}' \boldsymbol{W}_{k,t}\right)}{\Phi\left(\boldsymbol{\gamma}' \boldsymbol{W}_{k,t}\right)} \tag{20}$$

$$\mathrm{E}\left[Redeployed_{k,t+1} = 1 \middle| Idled_{k,t} = 1 \right] = \boldsymbol{\beta}_0^{'} \boldsymbol{X}_{k,t} + \sigma_1 \frac{\phi\left(\boldsymbol{\gamma}' \boldsymbol{W}_{k,t}\right)}{1 - \Phi\left(\boldsymbol{\gamma}' \boldsymbol{W}_{k,t}\right)}. \tag{21}$$

The ratios in the right side of Equations 20 and 21 are known as the inverse Mills ratio and its complement, respectively. They correct for the endogenous self-selection, and their values are derived from the first-stage selection model specified with Equation 16. Specifically, the term $\phi(\bullet)$ is the probability density function, $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution, and σ_0 and σ_1 are the associated coefficients to be estimated in this stage. The estimated coefficients on the inverse Mills ratio and its complement indicate the bias that would be present in the coefficient estimates if the endogeneity were not addressed (Heckman, 1979, Greene, 2003). To be clear, because Equation 20 is estimated only for non-idled rigs and Equation 21 is estimated only for idled rigs, the variable *Idled* is not included in either of these two models. The switching regression model still can test whether the likelihood of redeployment for idled rigs is higher compared to the likelihood of redeployment for non-idled rigs (*i.e.*, Hypothesis 1), which is deduced from the estimates of σ_0 and σ_1. Furthermore, because the variable *Inducement* is in vector $\boldsymbol{X}_{k,t}$ of covariates that affect redeployment, the model can test whether the effect of the inducement on redeployment is stronger for idled rigs than for non-idled rigs (*i.e*., Hypothesis 2). Likewise, because the variable *Redeployment cost* is in vector $\boldsymbol{X}_{k,t}$ of covariates that affect redeployment, the model enables the test of whether the effect of the redeployment cost on redeployment is stronger for idled rigs than for non-idled rigs (*i.e*., Hypothesis 3).

RESULTS

The empirical analysis begins with the descriptive statistics and a correlation table presented in Table 1. First, variance inflation factors (VIFs) were checked to ensure that multicollinearity is not a problem. All VIFs were below 10 with the mean VIF of 2.09 and a max of 3.55. The correlation matrix in Table 1 offers some initial evidence that idling is positively correlated with redeployment. In addition, the inducement is positively correlated with redeployment, while the redeployment cost is negatively correlated with redeployment, consistent with prior theory.

[Insert Table 1 about here]

Model 2 in Table 2 tests Hypothesis 1, which predicts the positive effect of idling on redeployment, using the specification in Equation 14 that does not account for endogeneity. The coefficient for *Idled* is positive and significant (p=.005). Models 3 and 4 use the 2SRI and report the first-stage regression expressed in Equation 16 and the second-stage regression expressed in Equation 17, respectively. In the first stage regression shown in Model 3, the instrument *Rivals cold stacking* significantly increases the likelihood that the focal rig is idled. The F-statistic of the instrument is 46.1, which is well above Staiger and Stock's (1997) threshold for a strong instrument (F-statistic >10). Whether this instrument is correlated with the second-stage outcome of redeployment is also checked, and they are unrelated (r=0.02, n.s.).

[Insert Table 2 about here]

In the second-stage regression in Model 4 of Table 2, the coefficient for *Idled* is positive and significant (p=.016) and is twice as large as in Model 2. The coefficient for the self-selection correction λ is also significant, thus suggesting that unobserved factors affecting idling could also affect redeployment (p=.008). The negative sign of the estimate for λ suggests a downward estimation bias tha appears in a simpler Model 2 that does not account for endogeneity. In other words, as also evident in the difference in estimates for *Idled* between Models 2 and 4, the model that does not account for endogeneity underestimates the effect of idling on redeployment. In particular, the effect of idling on the likelihood of redeployment after accounting for endogeneity is over 40% higher than estimating this effect without accounting for endogeneity.

Models 5 and 6 report the second-stage results based on the subsamples of idled and non-idled rigs respectively; both estimations correct for self-selection in each subsample using the switching regression model. In Model 5, the negative and significant coefficient estimate for λ (p=.002) indicates that the likelihood of redeployment for rigs that choose to be idled is greater than the likelihood of redeployment for all rigs with equivalent observable characteristics. This finding is consistent with the result in Model 4 involving the full sample. In Model 6, the coefficient estimate for λ is also negative but not significant.

Turning to Hypothesis 2, Models 5 and 6 together confirm the interaction hypothesized for the inducement. Specifically, for idled rigs, the estimated coefficient for *Inducement* is positive (b=.00198; p=.022), which indicates that the likelihood of redeployment for idled rigs increases as the inducement increases. For non-idled rigs, the coefficient for *Inducement* is also positive (b=.00095; p=.011). The positive effect that the inducement has on redeployment is stronger for idled rigs than for non-idled rigs: a unit increase in the inducement increases the probability of redeployment by about 59 percentage points more for idled rigs than for non-idled rigs.[8] The statistical significance of this difference in the estimates for *Inducement* between the two samples was tested, and the null hypothesis that these estimates are equal was rejected using the *suest* command in stata based on the nonlinear Wald test (p=.006).

Models 5 and 6 also provide empirical support for Hypothesis 3 related to the effects of the redeployment cost. As shown in Model 5 for idled rigs, the estimated coefficient for *Redeployment cost* is negative (b= -.0018, p=.009), which indicates that the odds of redeployment for idled rigs decrease as the

[8] For the average marginal effects of *Inducement*, a unit increase in this variable raises the probability of redeployment by about 0.11% for idled rigs and by about 0.045% for non-idled rigs.

redeployment cost increases. In Model 6 for non-idled rigs, the coefficient for *Redeployment cost* is also negative and significant (b= -.0016, p=.016). The negative effect that the redeployment cost has on redeployment is stronger for idled rigs than for non-idled rigs: a unit increase in the redeployment cost decreases the probability of redeployment by about 41 percentage points more for idled rigs than for non-idled rigs.[9] The coefficient estimates for the redeployment cost are significantly different between the two models: the null hypothesis that these estimates are equal was rejected using the *suest* command in stata based on the nonlinear Wald test (p=.001).

Finally, an additional robustness check was run with regard to the constructed choice set that a firm faces, to strengthen confidence in the results and interpretations. For each chosen well, a matched sample of unchosen wells with characteristics similar to the selected well was created (matched by their size, complexity, and geological formation). Doing this better accommodates any systematic differences existing between the selected well and other potential target wells, which can confound our diagnosis of our main effects on redeployment. Specifically, the coarsened exact matching (CEM) technique was used to match appropriate unselected target wells for each selected target well. Using such a matching technique essentially preprocesses the full choice sample by keeping those unrealized target wells that match on observable characteristics or dropping from the sample (or prune) those unrealized target wells that do not match The remaining data after CEM achieves better 'balance' between the treatment and control groups, which improves the data and estimation with less model dependence, lower bias, and increased efficiency (Iacus, King, & Porro, 2012; King & Zeng, 2006). After implementing this matching technique, the new sample consists of the 63,204 observations that were realized redeployment dyads (i.e., unchanged from the original sample) and 385,856 unrealized dyads (*i.e*., pruned from 942,695 in the original sample). Then with this retained matched sample using CEM, the main parametric estimation

[9] For the average marginal effects of *Redeployment cost*, a unit increase in this variable decreases the probability of redeployment by about 0.098% for idled rigs and by about 0.058% for non-idled rigs.

model of choice can be run, which is the conditional Probit model. When the analyses are run using the CEM sample, all hypotheses continue to be supported.

DISCUSSION

Contributions and implications

Resource allocation involves firms' choices to distribute their resources among alternative uses (Bower, 2016). Such choices are an integral part of the definition of strategy (Chandler, 1962) and are central to the fundamental issues in strategy (Maritan and Lee, 2017; Rumelt, Schendel, and Teece, 1994). To change allocation of their resources, firms use various real options (Trigeorgis, 1996). This study focuses on two resource allocation options considered in the literature, resource redeployment and resource idling. While significant research has been carried out in recent years on resource redeployment, far less is known about resource idling and how it potentially shapes resource redeployment. In particular, the existing theoretical and empirical study of options such as these was subject to the following general limitation that is addressed in this paper. Previous studies considered only one resource allocation option at a time. That approach failed to characterize how multiple options, such as resource redeployment and resource idling, are used in combination, and how they interact with each other.

Responding to this shortcoming, this study investigates empirically how resource idling and resource redeployment are used together and how they interact with each other. This research question is addressed in two steps. In the first step, research hypotheses are built by adding idling to existing formal models of redeployment, so that the modeled firm has options to idle and/or to redeploy its resources. The model first reveals that redeployment becomes more likely after idling. This increase in the likelihood of redeployment after idling also makes the use of redeployment more sensitive to its key determinants raised in previous research. In particular, the model derives that the previous idling strengthens both the positive effect of the inducement for redeployment and the negative effect of the cost of redeployment on the use of redeployment. In the second step, the study collects data on oil wells drilled in Texas over 25 years. The focal resource in this context is the rig of an oil-drilling firm that can be idled temporarily and/or redeployed to another field. Because resource idling is a choice that can precede and affect resource redeployment, a two-stage residual inclusion model controls for such selection into idling. The empirical results corroborate the formal predictions. Namely, redeployment of rigs is indeed more likely after those rigs were idled. The empirical evidence also indicates that the effect of resource idling is more pronounced when the endogenous nature of this resource allocation strategy is accommodated. Moreover, the previous idling of rigs increases both the positive effect of the inducement on the rig redeployment and the negative effect of the cost of such redeployment on the rig redeployment. The empirically confirmed theoretical results are also shown to be economically meaningful.

The chief contribution of this study is that it clarifies theoretically how two important resource allocation options, idling and redeployment, are used together and affect each other. Such clarifications have been repeatedly called for (Adner and Levinthal, 2004; Chi *et al*., 2019; Folta and O'Brien, 2004; Trigeorgis and Reuer, 2017; Vassolo, Anand, and Folta, 2004), but have been rarely attempted in existing theoretical or empirical research. Modeling option interactions complicates analytical models, and empirical investigation of multiple interacting options can also present data limitations that we have been able to overcome in this study. In the end, this paper develops compelling justification for the need to consider a portfolio of multiple resource allocation options available to a firm, instead of focusing on a single option at a time. The theoretically and empirically diagnosed interaction between idling and redeployment suggests that, when resource redeployment is predicted from its known determinants but resource idling is ignored, the effect of those determinants are systematically biased, thus providing researchers with incorrect estimates of the potency of those determinants.

Limitations and future research directions

In addition to the research opportunities identified in the discussion above, several directions exist to extend this research and address some of its limitations. To begin with, this study focuses on a bundle of resource idling and resource redeployment and, thus, is agnostic with respect to other real options that can be present to managers in various combinations. This focus on the two popular options, while abstracting from other combinations, is a pragmatic approach for making the first step to refine the understanding of such portfolios of resource allocation options. The formal theory in this study uses the existing model of resource redeployment and adds another option, resource idling. This combination is relevant to managers and interesting to researchers because idling is a lower-commitment strategy that is a natural precursor to the higher-commitment redeployment strategy that entails a bigger change to how the firm uses resources. Future research is encouraged to consider other combinations of options through which managers can contract, expand, and change the allocation of their firms' resources across various uses.

Another limitation is that, although this study expands the predominant focus of existing research on the allocation of capital to the consideration of nonfinancial resources, the empirical model directly captures the allocation of only one type of physical resources, rigs that firms use to drill oil wells. Meanwhile, industry press reports and interviews with executives in oil-drilling firms reveal that rig idling and rig redeployment can also involve human resources–crews of rigs that are subjected to such resource allocation strategies. It would be interesting and valuable for future resource allocation research to unpack the allocation of physical resources and the allocation of human resources. It would also be helpful to characterize the interplay of determinants of the allocation of various types of resources with each other.

Finally, the deliberate focus of this study on the development of reliable evidence of instances of resource allocation has come at a cost of abstracting from important organizational processes through which such allocation unfolds in firms. This study has the limitation of not considering how resource allocation choices are proposed and approved by various stakeholders, how features of organization design shape such decisions, and how cognitive biases potentially affect managerial choices about what resources to allocate and where to allocate them. It would be helpful if future in-depth studies used qualitative methods to elaborate such processes. Research in directions such as these could bring new insights into firms' flexible resource allocation strategies and the ways that different options to allocate resources are dynamically intertwined.

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Table 1. Correlations and summary statistics

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. *Redeployed*	1												
2. *Idled*	0.21	1											
3. *Inducement*	0.16	-0.07	1										
4. *Redeployment cost*	-0.11	0.03	-0.05	1									
5. *Uncertainty*	0.08	-0.04	0.01	0.01	1								
6. *Focal well complexity*	0.03	0.02	0.03	0.17	0.01	1							
7. *Target well complexity*	-0.02	-0.04	-0.01	-0.01	0.02	0.02	1						
8. *Rig field experience*	-0.07	-0.03	-0.00	0.02	0.01	0.01	-0.01	1					
9. *Rig performance*	-0.05	-0.02	-0.02	-0.01	0.00	-0.25	0.01	0.13	1				
10. *Rig profitability*	-0.03	-0.05	-0.03	-0.02	0.02	-0.04	0.02	0.20	0.16	1			
11. *Focal competitive density*	0.04	-0.01	0.02	0.01	0.03	-0.02	0.03	-0.01	0.04	-0.23	1		
12. *Target competitive density*	-0.01	0.00	-0.05	0.03	0.01	0.01	0.05	-0.02	0.02	0.01	-0.03	1	
13. *Rivals cold stacking*	0.02	0.28	-0.01	0.04	0.00	0.02	0.00	0.13	-0.03	0.07	-0.04	0.00	1
VIF (mean VIF = 2.088)	1.38	2.85	1.76	1.89	1.54	3.55	2.32	1.61	1.29	1.82	2.56	2.49	3.12
mean	0.056	0.21	1.19	218.4	0.502	2.001	1.905	54.12	0.499	17.49	13.05	14.5	87.2
S.D.	0.091	0.12	1.465	96.58	0.29	0.819	0.786	31.45	3.751	29.4	7.768	8.652	24.79

Table 2. Conditional Probit estimation (without and with correcting for endogeneity)

	CProbit Model (without correcting endogeneity)				CProbit Model (correcting endogeneity using 2SRI and switching regression models)							
	(1) DV: *Redeployed*		(2) DV: *Redeployed*		(3) DV: *Idled* (1st stage)		(4) DV: *Redeployed* (2nd Stage)		(5) DV: *Redeployed* (2nd Stage) Idled Sample		(6) DV: *Redeployed* (2nd Stage) Non-Idled Sample	
Constant	-2.599	*(.036)*	-2.406	*(.033)*	-0.358	*(.279)*	0.049	*(.421)*	-1.5904	*(.083)*	-1.969	*(.060)*
	(1.240)		(1.127)		(.3303)		(.061)		(.919)		(1.048)	
Rig profitability	-0.00025	*(.028)*	-0.00021	*(.032)*	-0.0040	*(.017)*	-0.0056	*(.076)*	-0.00307	*(.080)*	-0.00214	*(.211)*
	(.000112)		(.0001)		(.00168)		(.0031)		(.00175)		(.001713)	
Rig performance	-0.00043	*(.348)*	-0.00042	*(.359)*	-0.00108	*(.042)*	-0.00376	*(.042)*	-0.00062	*(.243)*	-0.00044	*(.061)*
	(.00046)		(.00046)		(.00053)		(.00185)		(.00053)		(.00023)	
Rig field experience	-0.00031	*(.003)*	-0.00027	*(.004)*	0.00209	*(.025)*	-0.00379	*(.004)*	-0.00477	*(.038)*	-0.00333	*(.077)*
	(.0001)		(.00009)		(.00093)		(.00131)		(.0023)		(.00189)	
Target well complexity	-0.008	*(.058)*	-0.0071	*(.052)*	-0.00016	*(.518)*	-0.0002	*(.065)*	-0.0022	*(.280)*	-0.0121	*(.112)*
	(.0042)		(.0037)		(.0002)		(.0001)		(.0020)		(.0081)	
Focal well complexity	0.0083	*(.033)*	0.0077	*(.027)*	0.00026	*(.281)*	0.0003	*(.012)*	0.0071	*(.008)*	0.0060	*(.035)*
	(.0039)		(.0035)		(.00024)		(.0001)		(.0030)		(.0031)	
Target competitive density	-0.00238	*(.531)*	-0.00082	*(.402)*	-0.00009	*(.706)*	-0.00016	*(.091)*	-0.00071	*(.031)*	-0.00181	*(.294)*
	(.00381)		(.00098)		(.00023)		(.0001)		(.00033)		(.00172)	
Focal competitive density	0.00418	*(.349)*	0.00373	*(.341)*	0.00006	*(.819)*	0.00024	*(.063)*	0.00027	*(.285)*	0.00049	*(.046)*
	(.00447)		(.00392)		(.00026)		(.00013)		(.00025)		(.000245)	
Uncertainty	0.99218	*(.025)*	0.98292	*(.022)*	-0.00264	*(.121)*	0.0527	*(.131)*	-1.235	*(.353)*	2.941	*(.175)*
	(.44258)		(.43012)		(.0017)		(.0349)		(1.328)		(2.168)	
Inducement	0.01125	*(.005)*	0.00997	*(.011)*	-0.0002	*(.191)*	0.0088	*(.016)*	0.00198	*(.022)*	0.00095	*(.011)*
	(.00403)		(.00392)		(.0001)		(.0037)		(.0009)		(.00038)	
Redeployment cost	-0.01812	*(.007)*	-0.01694	*(.010)*	0.00031	*(.167)*	-0.0068	*(.025)*	-0.0018	*(.009)*	-0.0016	*(.016)*
	(.00671)		(.00655)		(.00022)		(.00303)		(.0007)		(.00065)	
Rivals cold stacking					0.12748	*(.002)*						
					(.0419)							
λ (correction for self-selection)							-0.0726	*(.008)*	-0.081	(.002)	0.009	(.136)
							(.02725)		(.0263)		(.0062)	
Predictor*:*												

Idled		0.3019	*(.005)*		0.6128	*(.011)*		
		(.1081)			(.2423)			
Rig fixed effects	Yes	Yes			Yes		Yes	Yes
Year fixed effects	Yes	Yes			Yes		Yes	Yes
Pseudo/Adj R-squared	0.012	0.0125		0.0125	0.0236		0.0186	0.0280
N	1,005,901	1,005,901		1,005,901	1,005,901		663,894	342,007

Notes: **Models 1 and 2** are the baseline conditional Probit regressions where the main explanatory variable *Idled* is not adjusted for endogeneity. Pseudo R-squared is used here. The subsequent models uses a two-stage residual inclusion (2SRI) estimation approach that accounts for endogeneity for the main explanatory variable *Idled*. Specifically, **Model 3** is the first-stage Probit regression that includes the instrumental variable *Rivals cold stacking* to estimate the likelihood that the rig is idled. Adjusted R-squared is used here. **Model 4** is the second-stage Probit regression that includes the main explanatory variable *Idled* to estimate its effect on the likelihood of redeployment with the residual correction for self-selection included. Adjusted R-squared is used here. **Models 5 and 6** are alternative second-stage regressions using the subsamples of idled rigs and non-idled rigs, respectively, while correcting for self-selection in each sample based on the above first-stage estimation. Pseudo R-squared is used here. All models include rig and year fixed effects. The standard error is in parenthesis below each coefficient estimate, and the p-value is in parenthesis italicized to the right of each coefficient

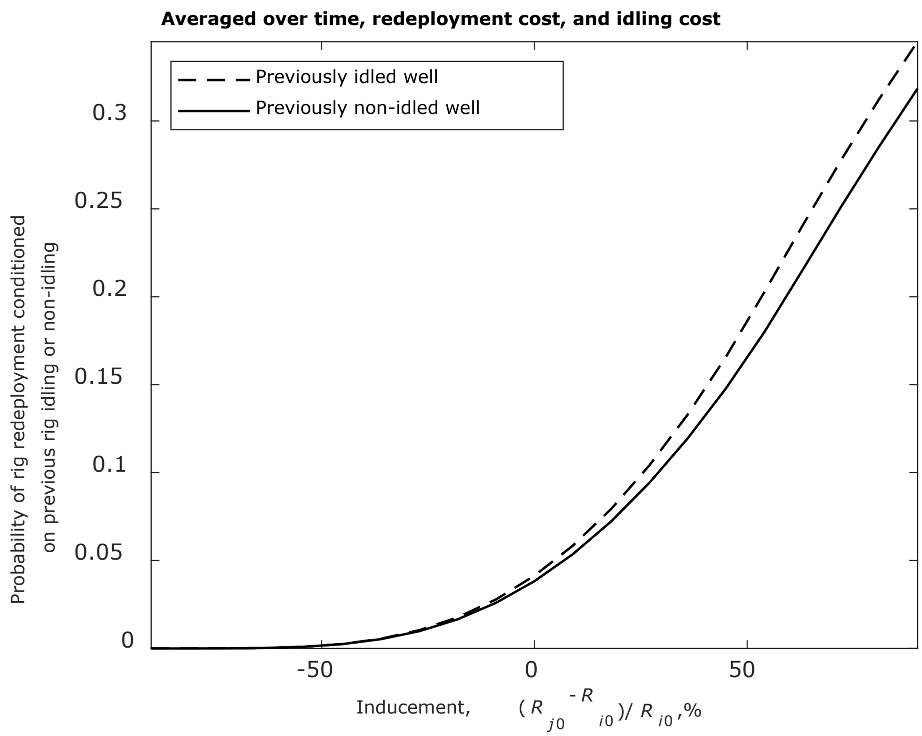
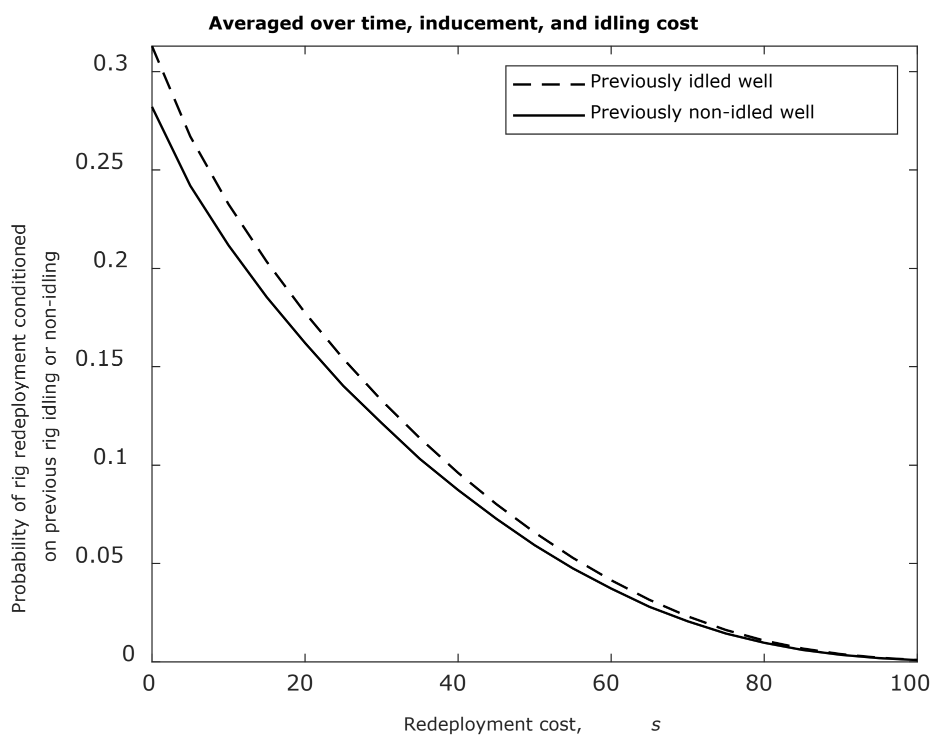


Figure 1. Effects of inducement on resource redeployment for idled and non-idled resources



FIigure 2. Effects of redeployment cost on resource redeployment for idled and non-idled resources