RESOURCE REDEPLOYMENT IN SINGLE-BUSINESS FIRMS: A THEORETICAL MODEL AND EMPIRICAL EVIDENCE FROM THE OIL-DRILLING INDUSTRY

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Abstract

Resource redeployment is an important and popular resource-allocation strategy that represents the withdrawal of resources from their original use and allocation to another use. Such redeployment has been elaborated conceptually and studied empirically. While resource redeployment has been studied exclusively in multi-business firms, single-business firms can also redeploy resources. Moreover, empirical studies have measured resource redeployment only indirectly, thus casting doubt on the extent to which managers use it and on its antecedents. Therefore, this study theoretically examines resource redeployment in single-business firms, and then empirically demonstrates resource redeployment and its determinants. To elaborate resource redeployment theoretically, this study builds a formal model of resource redeployment in a single-business firm. The model derives that redeployment is positively affected by the inducement, which is the current performance advantage of the new use over the original use, and by uncertainty in that performance. Resource redeployment is also negatively affected by the redeployment cost. In addition, uncertainty negatively moderates the effect of the inducement. To test these predictions, this study uses a unique dataset covering oil wells drilled in Texas. The to-be-redeployed resource in this context is the rig that is possessed by a driller, which can withdraw the rig from one field and reallocate it to another field. Performance is captured by the revenue on drilling contracts in each field. The redeployment cost is operationalized based on the geographical distance over which the rig needs to be transported. The empirical tests robustly confirm the four theoretical predictions.

Keywords: resource redeployment, real options, formal model, oil-drilling industry.

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INTRODUCTION

Resource allocation involves firms' choices to distribute their resources among alternative uses (Bower, 2016). Such allocation is fundamental to strategic management (Maritan and Lee, 2017; Rumelt, Schendel, and Teece, 1994) and is implemented by firms through the exercising of various real options (Trigeorgis, 1996). One option that firms often use to alter the allocation of their resources is resource redeployment, broadly defined as the withdrawal of various resources from their original use combined with their placement in another use. Developed initially in the military to describe the transfer of troops from one theater of war to another theater of war, the term was pioneered in management research by Anand and Singh (1997), who examined how diversified firms redeployed resources from one of their businesses to another business. Since this seminal work and introduction of the term to management research, resource redeployment in diversified, or multi-business, firms has been elaborated conceptually (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010; Lieberman, Lee, and Folta, 2017; Sakhartov, 2017; Sakhartov and Folta, 2014; 2015) and explored empirically (Anand, 2004; Anand and Singh, 1997; Giarratana and Santaló, 2020; Miller and Yang, 2016; Morandi Stagni, Santaló, and Giarratana, 2020; O'Brien and Folta, 2009; Wu, 2013). The importance of the concept of resource redeployment, as a type of resource allocation, can also be seen in the fact that it provides "a new justification for how multi-business firms create value" (Folta, Helfat, and Karim, 2016: 1).

This abundance of contributions on resource redeployment since Anand and Singh (1997) has firmly established the concept in management research. However, there are at least two directions in which research on resource redeployment can be further extended to complement and build upon existing contributions. First, although resource redeployment was indeed used to explain the performance of multi-business firms, this prevalent use does not necessarily imply that single-business firms do not have an option to redeploy their resources. For instance, Ahuja and Novelli (2016) noted that incumbent firms can redeploy their resources from an existing business model to a new business model when faced with an entrant having a disruptive innovation. Single-business firms can also redeploy resources across generations of products, geographic locations, technologies, customer segments, *etc*. Despite this recent recognition that resource redeployment is important to single-business firms too, studies have not systematically explored, conceptually or empirically, how single-business firms redeploy their resources.

Second, because resource redeployment is an internalized exchange, or transaction, that is not required to be reported in accounting documents comprising most empirical databases, such redeployment has been notoriously difficult to diagnose in secondary data (Folta *et al*., 2016: 11). As a result, even when theory concerned with redeployment of non-financial resources has been tested empirically, such redeployment is often captured only indirectly based on circumstantial evidence consistent with resource redeployment (*e.g*., contemporaneous changes in SIC codes reported by a firm or changes in the allocation of cash across a firm's business units) rather than by reliably registering redeployment of non-financial resources *per se*.[1] Such

[1] For example, O'Brien and Folta (2009) regarded resource redeployment as a mode of business exit and assumed that instances where one of the firm's primary-segment SIC codes (as reported in Compustat Segments) stopped being listed in the firm's reports reflected resource redeployment from that segment. Wu (2013) viewed resource redeployment as a mode of market entry and operationalized such redeployment as an addition of a new category of medical devices (as reported by the Center for Devices and Radiological Health of the U.S. Food and Drug Administration) by the firm that previously produced other categories. Anand (2004) and Anand and Singh (1997) considered resource redeployment an opportunity for a firm that operated in a declining product market (*i.e*., defense) to diversify to another product market (*i.e*., civilian), and operationalized such diversification as an acquisition of a civilian target by a defense firm based on SIC codes of these parties and on the data compiled by the Department of Defense. Miller and Yang (2016) operationalized resource redeployment as product turnover in a high-tech multiproduct firm wherein that firm drops one product and adds another product in the same year based on the product categories (as classified by CorpTech). Similarly, Lieberman *et al*. (2017) interpreted instances where firms in the telecommunications and Internet sector dropped the previously added product categories (as defined by CorpTech) to be consistent with resource redeployment. Morandi Stagni *et al*. (2020) used a 10-digit harmonized system (as defined by the World Customs Organization) to capture resource redeployment as the change in the allocation of cash to a business unit (*i.e*., in the difference between its capital expenditure and its own after-tax cash flow) in a diversified firm over a three-year period. Finally, Giarratana and Santaló (2020) measured redeployment of the shelf-space across product niches by firms in the drink industry as the growth in sales in a firm's segment (as classified by Euromonitor Passport) following a change in the tax conditions faced by that segment. Because those studies measured redeployment as the change in a firm's set of businesses, they assumed that such redeployment happened, instead of registering it directly.

indirect empirical operationalization of resource redeployment potentially risks confusing it with other resource allocation strategies such as divestitures (*e.g.*, Feldman and Sakhartov, 2021), or risks presuming resource redeployment as a strategic intent behind two concurrent, yet potentially independent decisions to withdraw and commit resources across products, markets, *etc*. The lack of a means of precisely and confidently identifying resource redeployment in large sample analyses can cast doubt on the extent to which it is actually carried out by managers (Folta *et al*., 2016: 11). All of these empirical challenges that flow from the data limitations surrounding resource redeployment can also undermine conclusions on its determinants and consequences in different strategy contexts.

Therefore, the primary purpose of this study is to empirically investigate resource redeployment in single-business firms by reliably demonstrating its occurrence. This purpose, in turn, helps this study explain resource redeployment choices with attributes of the empirical context in which they are made. To achieve these objectives, the study uses a sample of oil drilling in Texas over twelve years. The resource that is a candidate for redeployment in this context is the rig, which resembles a tall derrick that runs a motor to spin a drill pipe into the ground for drilling and is possessed by a single-business firm called an oil-drilling contractor. The rig is mobile: it can be withdrawn from the well in which it was used located in one geological market known as a field, and reallocated to another well in another field. The first contextual factor figuring into such redeployment decisions is the inducement to redeploy the rig from the original field to another field, namely whether and to what extent the revenue on a drilling contract would be higher in the new field than in the original field. This inducement acts as an opportunity cost to continuing the original use of resources (Levinthal and Wu, 2010). The second contextual factor is the uncertainty about the revenue on the drilling contracts. Such uncertainty spurs future scenarios in which redeployment becomes profitable (Trigeorgis, 1996), thus enabling future redeployments (Sakhartov and Folta, 2015). The third contextual factor is the redeployment cost the oil-drilling contractor would bear when removing the rig from the original well and reallocating it to a well in the new field, thus losing some efficiency in the resource use (Montgomery and Wernerfelt, 1988).

In order to develop research hypotheses for testing whether and how these factors influence resource redeployment, this study first adapts previous formal models of such choices in multi-business firms (Feldman and Sakhartov, 2021) to the present empirical context of oil drilling. More specifically, the adapted model considers a single-business firm that can redeploy its resources (*i.e.*, the rig) to another location. In this context, as the model will demonstrate, the resource-redeployment choice is monotonically positively affected by the inducement and by uncertainty and is monotonically negatively affected by the redeployment cost. The first effect takes place because the inducement increases the opportunity cost for the oil-drilling contractor to continue operations in the field that *currently* performs worse than the alternative field. The second effect occurs because uncertainty promotes scenarios where the original field will underperform the alternative field *in the future*. The third effect holds because the redeployment cost diminishes the net cash flow that accrues to the oil-drilling contractor upon the redeployment of the rig. In addition, uncertainty negatively moderates the positive effect of the inducement on redeployment. This interaction emerges because uncertainty makes future redeployment of the rigs more attractive than the present redeployment, even in the presence of a positive inducement, thus muting the effect of the inducement on redeployment. The empirical analyses in this study provide evidence in accord with the four hypotheses.

The first and primary contribution of this paper is that it provides a detailed and careful empirical operationalization of resource redeployment, an important and popular resource-allocation strategy. There is no doubt in attributing the use of rigs on new oil wells to resource redeployment because each rig is known to have been dismantled from the original well, to have been moved to a different field, and to have been reassembled on another well. This identification of the instances of resource redeployment (and of the lack of such instances), in turn, provides confidence not only in the extent of resource redeployment but also in the determinants of resource redeployment. In addition, the unique combination of formal theorizing and empirical analysis provides a compelling elaboration and corroboration of the theory of resource redeployment. By using a formal model to adapt models of resource redeployment in multi-business firms to the case of a single-business firm, the study also is able to offer a set of theoretical predictions that are aligned to the empirical context. The next section presents all the four hypotheses that are tested in the subsequent empirical analyses.

THEORETICAL PREDICTIONS

Research hypotheses for the specific context of resource redeployment in this study are developed by adapting a previous formal model of resource redeployment in multi-business firms (Feldman and Sakhartov, 2021). The adapted model considers an oil-drilling firm that previously used its rig on the oil well located in the original field. Specifically, before time $t=0$ that reflects the present in the model, the firm used its rig in field i; and this starting point is denoted in the model as $m_{i0-\partial t}=1$. At any time before the rig fully depreciates at the terminal time $t=T$, the firm can redeploy its rig to the alternative field j or can continue to use the rig in the original field i if such redeployment did not already occur in the past. If redeployment to the alternative field j happens at time t, the firm's choice as to where its rig is used switches from $m_{it-\partial t}=1$ to $m_{it}=0$. If, alternatively, the firm stays in in the original field i, the model is agnostic with regard to whether redeployment of the rig happens within that field (*i.e.*, the revenue is specific to the field which represents the local market in this case). The model consists of four parts: (1) a specification of revenue the firm can generate by using its rig in each of the two fields, (2) a specification of the redeployment option, (3) a description of how the firm uses this option, and (4) a presentation of results. These parts are described in turn below.

Revenues in two fields

Revenue that the firm can generate in each of the two fields is uncertain. This uncertainty is reflected in 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 receives per unit of time by using its rig in fields i and j respectively, R_{i0} and R_{j0} are present (*i.e.*, at present time $t=0$) rates of revenues the firm receives per unit of time by using its rig in fields i and j respectively; μ_i and μ_j are drifts for these revenues; σ_i and σ_j are volatilities of the revenues that capture uncertainty; and W_{it} and W_{jt} are Brownian motions with correlation ρ. This specification is prevalent in modeling real options in general and resource redeployment in particular (*e.g.*, Feldman and Sakhartov, 2021; Sakhartov and Folta, 2014; 2015) because it makes a reasonable assumption that the two random variables, R_{it} and R_{jt}, are more difficult to predict the farther they are projected into the future.

Redeployment option

If the firm redeploys its 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 redeployment coefficient s and the current realization R_{jt}^y of the current rate of revenue R_{jt} on the destination field, thus showing the loss in the rate of revenue due to redeployment. Formally,

$$S_t^y = \mathbf{1}_{(m_{it}=0,m_{it-\partial t}=1)} sR_{jt}^y . \qquad (4)$$

Term $\mathbf{1}_{(m_{it}=0,m_{it-\partial t}=1)}$ in Equation 4 is a dummy that is equal one only when redeployment was not committed before the current time t and happens at the current time t. Equation 4 leads to the following statement of the expected net present value V_t^{yS} of the firm that starts using the rig in the alternative field at time t:

$$V_t^{yS} = \left(-S_t^y + R_{jt}^y - C_j\right)\partial t + e^{-r\partial t} E^{P^j}\left[V_{t+\partial t}^{yS} \mid \left(m_{it}^* = 0, y\right)\right]. \qquad (5)$$

In Equation 5, C_j is the rate of operating costs (other than the redeployment cost S_t^y) the firm would incur per unit of time by using its rig in field j, $E^{P^j}\left[V_{t+\partial t}^{yS} \mid \left(m_{it}^* = 0, y\right)\right]$ is the expectation with respect to the probability distribution P^j that the random variable R_{jt} follows, r is a risk-free interest rate, and $V_{t+\partial t}^{yS}$ is the firm's net present value in the immediate next time $(t+\partial t)$.

Expectation $E^{P^j}\left[\cdot\right]$ is conditioned on the current or the past choice to redeploy the rig $(m_{it}^* = 0)$.

This expectation is assessed when revenue R_{jt} is in state y.

Use of redeployment option

Redeployment of the rig to the alternative field is an option, rather than an obligation, for the firm. This option is exercised by the firm only if doing so makes the firm better off. A natural alternative available to the firm that is still using its resources in the original field is to continue doing so. When current realizations for R_{it} and R_{jt} are R_{it}^x and R_{jt}^y respectively, the expected net present value V_t^{xy0} for the firm that keeps deploying its rig in the original field is as follows:

$$V_t^{xy0} = \left(R_{it}^x - C_i\right)\partial t + e^{-r\partial t} E^{P^{ij}}\left[V_{t+\partial t}^{xy} \mid \left(m_{it}^* = 1, x, y\right)\right]. \quad (6)$$

In Equation 6, C_i is the rate of operating costs the firm would incur per unit of time by using its rig in field i, $V_{t+\partial t}^{xy0}$ is the net present value of the firm in the immediate next time $(t+\partial t)$.

Expectation $E^{P^{ij}}\left[V_{t+\partial t}^{xy} \mid \left(m_{it}^* = 1, x, y\right)\right]$ is taken with respect to the probability distribution P^{ij} for R_{it} and R_{jt} and is conditioned on the current choice to keep the original rig allocation (*i.e.*, $m_{it}^* = 1$). The expectation is estimated when R_{it} and R_{jt} are in their respective states x and y.

Combining Equations 5 and 6, the firm's net present value V_t^{xy} is as follows:

$$V_t^{xy} = \max_{m_{it}} \left\{V_t^{yS}, V_t^{xy0}\right\}. \quad (7)$$

Accordingly, the firm's current choice $m_{it}^* \in \{0,1\}$ can be expressed in the following way:

$$\left(m_{it}^* \middle| m_{it-\partial t}\right) = \arg\max_{m_{it}} \left\{V_t^{yS}, V_t^{xy0}\right\}. \quad (8)$$

Equations 5 and 6 are Bellman equations (Bellman, 1957) that consider the dynamic implications of the current choice m_{it}^* (*i.e.*, how that choice affects not only the current cash flow but also the future cash flows). Therefore, Equations 7 and 8 are also Bellman equations that cast the firm's resource allocation choice m_{it}^* as dynamically optimal. Dynamic optimality demands that the firm choose the best time to exercise the redeployment option. This setting makes the firm compare: (a) the value of continuing to hold the redeployment option if it has not been exercised yet and (b) the value of exercising the redeployment option if it has not been exercised yet. If the firm has already exercised the redeployment option, the firm keeps the rig in the destination field until the full depreciation of the rig.

The above Bellman equations split the problem of resource redeployment into a sequence of sub-problems that are amenable to a numerical solution. Such choices are expressed in a recursive form that relies on backward induction to derive optimal conditional choices $\left(m_{it}^* \middle| m_{it-\partial t}\right)$ at all times t and with all values of R_{it}^x, and R_{jt}^y. The solution involves the discretization of the continuous-time distribution P^{ij} specified with Equations 1–3. Like Feldman and Sakhartov (2021), this model uses the popular and efficient discretization developed 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 $R_{jt+\partial t}$ take four 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}.[2] With this, expectations in Equations 5 and 6 are estimated as $E\left[V_{t+\partial t}^{xy0}\right] = q^{uu}V_{t+\partial t}^{uu0} + q^{ud}V_{t+\partial t}^{ud0} + q^{du}V_{t+\partial t}^{du0} + q^{dd}V_{t+\partial t}^{dd0}$, $E\left[V_{t+\partial t}^{yS}\right] = (q^{uu} + q^{ud})V_{t+\partial t}^{uS} + (q^{du} + q^{dd})V_{t+\partial t}^{dS}$.

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

The backward induction procedure starts at the penultimate time $t = T - \partial t$ with the terminal conditions $V_T^{xy0} = 0$ and $V_T^{yS} = 0$ 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 present time $t = 0$. At this point in the estimation, the model returns the net present value of the firm V_0^{xy}, but all of the firm's resource-allocation choices over the lifecycle of the rig are still characterized as conditional $\left(m_{it}^* \middle| m_{it-\partial t}\right)$. Because the firm is known to have initially used its rig in the original field ($m_{i0-\partial t} = 1$), the model can now change the direction for going through the lattice and follows recursively forward in time until it reaches the penultimate time $t = T - \partial t$ when the firm can make its last resource-allocation choice (*i.e.*, like in Feldman and Sakhartov, 2021). In each step going forward in time and for each combination of revenues R_{it}^x, and R_{jt}^y, the model derives unconditional choice m_{it}^* based on the known immediate previous choice $m_{it-\partial t}$ and on the optimal conditional decision $\left(m_{it}^* \middle| m_{it-\partial t}\right)$ recovered with the backward induction. Finally, the resulting three-dimensional matrix (*i.e.*, with t, x, and y being the three dimensions) that is generated for m_{it}^* enables the following analyses.

Formal results

The empirically testable predictions involve three determinants of resource redeployment that are present in this context. The first contextual factor 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 the alternative field than in the original field. The second contextual factor is the uncertainty about the revenue on the drilling contracts. The third determinant is the redeployment costs the firm would bear when removing the rig from the original field and reallocating it to another field.

Results of the formal model are summarized visually in three figures presented in this section, and verbally in four hypotheses concluding the section. Figure 1 presents implications of the inducement and of the redeployment cost for the rig redeployment. The variation of color in the contour map reflects the probability of the rig redeployment. The horizontal axis spans values of the redeployment cost, whereas the vertical axis shows the inducement. The first observation in Figure 1 is that it changes color from blue to red in the direction from the bottom to the top. This result suggests that the probability of the rig redeployment monotonically increases in the inducement. The monotonic positive effect of the inducement on the rig redeployment occurs because the inducement increases the opportunity cost for the firm to continue drilling operations in the field that *currently* performs worse than an alternative field. Another observation in Figure 1 is that it changes color from red to blue in the direction from the left margin to the right margin. This result suggests that the probability of the rig redeployment monotonically declines in the redeployment cost. The monotonic negative effect of the redeployment cost on the rig redeployment holds because the redeployment cost diminishes the net cash flow that the firm would receive following the redeployment of the rig. Finally, the topography of the filled contour map shows no evidence of the reversal of either of the two effects or of the considerable change in the magnitude of one of the effects with different levels of another parameter. Accordingly, there seems to be no significant interaction between the inducement and the redeployment cost in determining the likelihood of the rig redeployment.[3]

[3] The response variable in Figure 1, which is reflected in the variation of color in that filled contour map and which is scaled in the side bar to the right of that map, is the cumulative probability that the firm will have redeployed its rig to the alternative field by time $t = 3/4T$ (*i.e.*, during the first three quarters of the rig's lifecycle). This cumulative probability aggregates all

****Insert Figure 1 about here****

Figure 2 demonstrates implications of uncertainty and of the redeployment cost for the rig redeployment. The variation of color in Figure 2 again shows the probability of the rig redeployment. The horizontal axis captures the redeployment cost, while the vertical axis represents uncertainty. The key pattern evident in Figure 2 is that it alters color from blue to red in the direction from the bottom to the top, thus suggesting that the odds of the rig redeployment increase in uncertainty. This positive effect takes place because uncertainty propels scenarios where the original field will underperform the alternative field *in the future*. Thus, like the effects of inducements in Figure 1, uncertainty introduces the opportunity cost of staying in the underperforming original field, but does so in some future scenarios for the revenues in the two fields. Also, Figure 2 corroborates the result diagnosed in Figure 1 that the odds of the rig redeployment decline in the redeployment cost. Finally, Figure 2 provides no evidence of the reversal of either of the two effects or of the considerable change in the magnitude of one of them with different levels of another parameter. Thus, there is no significant interaction between uncertainty and the redeployment cost in determining the odds of the rig redeployment.[4]

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redeployment choices the firm would make during time $t \in \left[0,\ 3/4\,T\right]$ and across all possible realizations x and y for R_{it}^{x}, and R_{jt}^{y} during that time interval. The horizontal axis in Figure 1 spans values of the redeployment cost $s \in \left[0, 100\right]$; whereas the vertical axis involves values of the inducement $\left(R_{j0} - R_{i0}\right)/R_{i0} \in \left[0\%, 200\%\right]$ that result from $R_{i0} = 0.08$ and $R_{j0} \in \left[0.08, 0.24\right]$. Parameters that are ancilary for the analyses in Figure 1 take the following values: $\sigma_i = \sigma_j = 0.5$, $\rho = 0$, $C_i = C_j = 0.07$, $r = 0.08$, $T = 1$, and $N = 200$.

[4] Like in Figure 1, the response variable in Figure 2, which is shown in the variation of color in that filled contour map and which is scaled in the side bar to the right of that map, is the cumulative probability that the firm will have redeployed its rig to the alternative field by time $t = 3/4T$. Also, like in Figure 1, the horizontal axis in Figure 2 covers values of the redeployment cost $s \in \left[0, 100\right]$. The vertical axis in Figure 2 reflects uncertainty by spanning values of the revenues' volatilities $\sigma_i = \sigma_j \in \left[0.05, 1.05\right]$ that are set equal between the two wells, to reduce the number of analyzed parameters and to simplify the analyses. Parameters that are ancilary for the analyses in Figure 2 take the following values: $R_{i0} = R_{j0} = 0.08$, $\rho = 0$, $C_i = C_j = 0.07$, $r = 0.08$, $T = 1$, and $N = 200$.

****Insert Figure 2 about here****

For completeness, Figure 3 visualizes the effects of uncertainty and of the inducement on redeployment. The variation of color in Panel A of Figure 3 continues to show the probability of redeployment. The horizontal axis characterizes the inducement, while the vertical axis shows uncertainty. Three patterns in Panel A are noteworthy. First, the contour map alters color from blue to red in the direction from the left margin to the right margin, thus validating the result in Figure 1 that the probability of the rig redeployment increases in the inducement. Second, close to the left margin of Panel A where the inducement is relatively low, the map changes its color from blue to green in the direction from the bottom to the top, thus confirming the previous observation that the odds of the rig redeployment grow in uncertainty. Third, in the middle of Panel A where the inducement becomes moderate, the map changes its color from red to orange or yellow in the direction from the bottom to the top, thus revealing that the odds of the rig redeployment declines in uncertainty. Thus, the positive effect of uncertainty diagnosed in Figure 2 for the low imducement and validated in the left part of Panel A in Figure 3 gets reversed to negative when the inducement is not low in Panel A of Figure 3. This reversal demonstrates a significant interaction between the two determinants that is further analyzed below.[5]

****Insert Figure 3 about here****

[5] Like in Figures 1 and 2, the response variable in all panels of Figure 3 is the cumulative probability that the firm will have redeployed its rig to the alternative field by time $t = 3/4T$. The horizontal axes in Panels A and B of Figure 3 involve values of the inducement $\left(R_{j0} - R_{i0}\right)/R_{i0} \in \left[0\%, 200\%\right]$ that result from $R_{i0} = 0.08$ and $R_{j0} \in \left[0.08, 0.24\right]$. The vertical axis in Panel A of Figure 3 reflects uncertainty by covering values of the revenues' volatilities $\sigma_i = \sigma_j \in \left[0.05, 1.05\right]$. In Panel B of Figure 3, "Low uncertainty" correesponds to $\sigma_i = \sigma_j = 0.05;$ "Medium uncertainty" is $\sigma_i = \sigma_j = 0.55;$ and "High uncertainty" is $\sigma_i = \sigma_j = 1.05.$ In Panel C of Figure 3, "Low inducement" is $\left(R_{j0} - R_{i0}\right)/R_{i0} = 0\%$; "Medium inducement" is $\left(R_{j0} - R_{i0}\right)/R_{i0} = 100\%$; and "High inducement" is $\left(R_{j0} - R_{i0}\right)/R_{i0} = 200\%$. Parameters that are ancilary for the analyses in Figure 3 take the following values: $s = 5$, $\rho = 0$, $C_i = C_j = 0.07$, $r = 0.08$, $T = 1$, and $N = 200$.

Panel B in Figure 3 dissects the three-dimensional surface shown in various colors in Panel A at three levels of uncertainty. The blue line in Panel B has a more-positive slope than the green line, which in turn has a more-positive slope than the red line in the same panel. Accordingly, there is a robust pattern with which uncertainty negatively moderates the positive effect of the inducement on the probability of the rig redeployment. This nonintuitive interaction occurs because uncertainty makes future redeployment of the rig more attractive than the present redeployment even in the presence of a nontrivial current advantage in the alternative field (*i.e.*, the inducement), thus suppressing the effect of the inducement on the odds of the rig redeployment. This negative interaction is so strong that it can reverses the ultimate effect of uncertainty from positive to negative, as the green line in Panel C of Figure 3 demonstrates. An additional observation in all panels of Figure 3 is that high levels of the inducement can make the probability of the rig redeployment insensitive to uncertainty. This happens because a very high revenue advantage in the alternative field makes the firm immediately redeploy the rig, regardless of future uncertain opportunities.

The four most robust patterns that are demonstrated in Figures 1−3, can be summarized as the following four hypotheses that are tested in the subsequent empirical analyses.

Hypothesis 1: The inducement positively affects the probability of the rig redeployment.

Hypothesis 2: The redeployment cost negatively affects the probability of the rig redeployment.

Hypothesis 3: Uncertainty positively affects the probability of the rig redeployment.

Hypothesis 4: Uncertainty negatively moderates the positive effect of the inducement on the probability of the rig redeployment.

EMPIRICAL TESTING

Empirical context: The onshore oil drilling industry

To empirically study resource redeployment, this study focuses on decisions to redeploy drilling rigs in the onshore oil drilling industry. Oil reserves are found in distinct geologic formations that lie beneath the earth's surface, and the mission of a production company who owns a particular well site where these reserves are buried is to extract them for processing and sale. An area's reserves are typically buried under many layers of rock that do not contain oil. The objective of drilling a well is to penetrate these overlying rock layers to reach the oil in the field. An oil field is created when oil reserves are discovered during the initial exploration process carried out by producers. The geology in a given field is quite homogenous; yet there is significant geologic variation across fields, where oil prospects are controlled by different sets of geological circumstances, as the types of rock encountered in one area will generally not be the same as those encountered elsewhere. Across these fields, the geologic composition of the rocks that must be drilled through—for instance, multiple layers of sandstone, shale, and limestone—varies considerably from the surface to its targeted depth.

The drilling of a well is carried out by the contracted driller's rig and its employed drilling crew. Rigs are mobile so they can change locations between well sites, but moves of more than 50 miles typically require several days and can incur substantial transportation costs. When under contract, rigs operate 24 hours per day and 7 days per week, rotating crews in three 8-hour shifts. The industry is vertically disintegrated due to the spatial and temporal variation with which producers develop wells. Drilling activities fluctuate with the producers successfully finding new fields, and also with oil prices. Any successful exploration then requires drilling development wells, while unsuccessful explorations resulting in dry holes do not. The nonspecificity 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. This smoothing minimizes overall rig capacity requirements, as well as rig transportation and mobilization costs, without requiring the producers to contract directly with each other. Producers typically contract with rigs for the drilling of one well at a time. Drillers are actively looking for new opportunities from producers for their rigs to be put to work, and their rigs are often being redeployed from previously completed wells to new wells that are opening up for development, even before opportunities in the current field are exhausted. Delay in drilling a given well usually arise when the chosen driller's rig is located further away from that well site and requires more time to be moved.

The oil drilling industry is well suited to empirically study redeployment for several reasons. First, resource redeployment is a critical strategy used by drillers to optimize opportunities for their rigs. Such driller's action allows its rig to be physically closer to an available well and thus more attractive to its potential client, because any setup cost and time to commence drilling operations is reduced compared to rigs that are located further away. This empirical context allows this study to observe redeployment by tracking the movements of every rig from a well in its home oil field (or home market) to a new well located in an outside oil field (or outside market). Every oil field can be considered a unique market because the opportunity set can vary from another field depending on the availability of undrilled wells and the potential client producers operating there. Second, the important determinants for resource redeployment according to the literature—the inducement, the redeployment cost, and the uncertainty—are key considerations for drillers in making such decisions. As explained below, the empirical context allows this study to capture these factors. Finally, the context provides evidence that such redeployments take place prior to the firm securing their pursued deals (and not after securing work for these projects). Otherwise, redeployments happening after the driller secures the project could confound the underlying incentives, costs, and risks in exercising such options because such redeployment can be compensated by the client producer.

Data and sample

The sample is based on data from DrillingInfo, RigData, and the Texas Railroad Commission (TRC), the regulatory commission responsible for all oil and gas drilling in the state. In addition, macro-level data on oil prices and weekly U.S. demand and supply levels are taken from the Energy Information Administration. These combined data covering 12 years between 1999 and 2011 consist of detailed information about the characteristics of all available wells in the state, those that are eventually drilled, and every rig that drilled them. Accordingly, the data allow this study to track the movements of rigs between well sites.

The empirical analysis requires the definition of the sample and the structuring of the data to study the decision problem of resource redeployment, which is conceptualized as follows. When a firm's rig becomes available at a focal well, the firm faces a decision problem of whether to drill another well in the same field or to redeploy the rig to a new target well outside the current field. A firm thus enters the sample when its rig becomes available for redeployment. The choice set of potential target wells for redeployment is then defined as the set of wells in Texas outside the current oil field, in which the rig is located. As a result, a choice set of potential redeployment dyads between the original well and all potential redeployment target wells is constructed by creating a set of realized and unrealized dyads between the field of the original well and potential alternative fields. Importantly, the explanatory variables resulting from this design are based on data that precede the redeployment decision, thus creating a naturally lagged temporal structure, which helps with identification and mitigates endogeneity concerns (elaborated below in the section entitled "Analytical approach"). Following this empirical design, the final sample used in analyses comprises 2,080,672 observations, which are potential redeployment decisions every month over the twelve years in the sample. In this choice set during the sample period, 108,281 observations are realized dyads in terms of instances of redeployment and the remaining 1,972,391 observations are unrealized dyads that are together associated with 1,355 rigs that are owned by 168 drillers that operate purely in the drilling business.

Variables

Dependent variable

The dependent variable, *Redeployed*, registers whether or not the drilling rig is moved from the oil well in its original field to a well in a different oil field. For the focal rig, the choice set of potential target wells, to which the rig can be redeployed, includes all available wells located outside the original field. *Redeployed* is set to equal to one in the dyad of wells when the rig is actually moved between their fields, and zero otherwise. Rig moves within the same oil field, where wells are located much more proximately to each other, are not considered redeployment due to the relatively homogenous characteristics (*i.e.*, payment to the contractor, the redeployment cost, and uncertainty) of these wells.

Explanatory variables

The first explanatory variable, *Inducement*, should capture the difference between the potential payment for work on the target well to which the rig can be redeployed and the most recent payment the contractor received in using its rig on the current well. This variable is measured for each dyad associated with the rig's original well and the potential alternative well. Specifically, the payment to the contractor on the current well is calculated as the price per foot paid to the contractor in drilling that well (in hundreds of dollars). The expected payment for each potential target well is calculated as the average price per foot drilled paid to drillers for recently completing nearby wells in the same field as the target well (in hundreds of dollars). The driller estimates the expected payment for the potential target by relying on nearby completed wells because the target well's actual payment is not realized until after the project is under contract. The nearby wells used in this operationalization are set to be within a 25-mile radius of the target well and to be completed in the same year as the one targeted for potential redeployment.

The second explanatory variable, *Redeployment cost*, is measured as the geographical distance between the site of the rig's current well and the site of the potential well (in miles). Moves for more than 50 miles typically require several days and involve substantial transportation costs. For instance, based on 2011 trucking data for the last year in our sample, the trucking fee for transporting a standard drilling rig was about $130,000 for every 25 miles. According to industry insiders, the primary cost driver of rig redeployment is in transportation, whereas a small fraction is in disassembling the rig pre-move and reassembling it post-move.

The third explanatory variable, *Uncertainty*, measures the degree of unpredictability of revenue generated on the potential target well. Such uncertainty captures the degree to which revenue on the well diverges from the level that would be rationally predicted based on available historical information. Accordingly, the conditional variance generated from generalized autoregressive conditional heteroskedasticity (GARCH model) is used to capture uncertainty. This statistical modeling technique is often used to predict uncertainty of asset returns (Bollerslev, 1986; Greene, 2003). Specifically, the expected revenue is calculated for each potential target well in each month 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, which generates time series data for each target well's return over the sample 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. Finally, the estimated conditional variance captures the uncertainty that is not predictable about any trend that might exist for each period in the time series.

Control variables

Several control variables, which account for other determinants of redeployment, are included to mitigate concerns of omitted variable bias. First, *Focal well complexity* and *Target well complexity* are added to the model specifications. More technically complex projects pose greater challenges to effectively drill and also entail greater risks of accidents occurring. As a result, a rig working on a more complex well is more likely to seek more manageable projects elsewhere, while a rig's potential target well that is more complex is less likely to be chosen. The complexity of the rig's current well is measured 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. The same scale is used to measure the complexity of potential target wells.

Second, a rig with greater experience in a given market can be more efficient operating in that market, such as operating with lower costs and achieving earlier completion times, due to its crew members having better knowledge of the geological terrain, such familiarity drilling through the different rock stratifications, compared to those with less experience. 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 current oil field is less likely to be redeployed to an outside market. Accordingly, *Rig field experience* is measured as the number of previous wells drilled and completed in the rig's current field.

Third, *Rig performance* may be a significant predictor of its redeployment. Such performance is assessed using the rig's drilling speed, the primary metric with which drillers are evaluated in the industry (Kellogg, 2011). Following past literature, a rig's drilling speed is estimated by taking the total depth of the current well and then dividing it by the total number of drilling days needed to complete the well (using the drilling commencement and completion dates). 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, & Yeung, 2013; Pacheco-de-Almeida, Hawk, & 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.[6]

[6] 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 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.

Then, *Rig profit* is included. A rig that has been more profitable in its home market has less incentives to leave for a new market. A rig's profitability is measured as the average profit made for its previously drilled wells in its home field, which is based on the revenue earned for each of its wells minus the driller's total cost in drilling those wells.

Next, *Focal competitive density* is incorporated. The intensity of competition that a driller's rig faces from rival drillers in its home market can lead it to pursue opportunities in other, less contended locations. The competitive density is proxied based on the number of rival drillers operating within a 25-mile radius relative to the focal rig.

Likewise, *Target competitive density* is accounted for in the specifications. As a driller considers potential target wells for redeployment, the competitive density of a potential site can deter it from redeploying a rig there. For each potential site, its competitive density is measured by counting the number of rival rigs operating within a 25-mile radius to the potential well site. Finally, a series of fixed effects for year and driller is added to account for differences across time and firms.

Analytical approach

The model specification is built to examine the determinants of redeployment decisions. Specifically, this study seeks to establish whether the inducement, the redeployment cost, and uncertainty affect the driller's decision to redeploy its rig from one well to another well in a different field. This examination uses the following conditional probit model specification:

$$\Pr\left(Redeployed = 1\right) = \Phi\begin{pmatrix} \beta_0 + \beta_1 Inducement + \beta_2 Redeployment\, cost + \\ \beta_3 Uncertainty + \boldsymbol{\beta_4 X} \end{pmatrix} \tag{9}$$

In Equation 9, *Redeployed* is the dependent variable as specified above; $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution; *Inducement*, *Redeployment cost*, and

Uncertainty are the three explanatory variables as described above; and $\boldsymbol{X}$ is a vector of control variables as noted above. Equation 9 is subjected to the maximum likelihood estimation. The first expected direct effect, which is based on Hypothesis 1, is that the inducement has a positive impact on the probability of redeployment, thus yielding $\beta_1 > 0$. The second expected direct effect, which is based on Hypothesis 2, is that the redeployment costs has a negative impact on the probability of redeployment, thus yielding $\beta_2 < 0$. The third expected direct effect, which is based on Hypothesis 3, is that uncertainty has a positive impact on the probability of redeployment, thus yielding $\beta_3 > 0$.

The last expected interaction effect, which is based on Hypothesis 4, is that uncertainty negatively moderates the positive effect of the inducement on the probability of redeployment. To test this possibility, we make the marginal effect of inducement to be a function of the uncertainty in the market as follows:

$$\beta_1 = \alpha_0 + \alpha_1 Uncertainty \tag{10}$$

Substituting Equation 10 into Equation 9 yields the following expression:

$$\Pr\left(Redeployed = 1\right) = \Phi\begin{pmatrix} \beta_0 + \alpha_0 Inducement + \alpha_1 Uncertainty * Inducement + \\ \beta_2 Redeployment\ cost + \beta_3 Uncertainty + \boldsymbol{\beta_4 X} \end{pmatrix} \tag{11}$$

Because Hypothesis 4 predicts that uncertainty negatively moderates the positive effect of the inducement, the expected signs for the estimates are $\alpha_0 > 0$ and $\alpha_1 < 0$.

As a summary of this analytical approach, the empirical objective is to estimate the direct impacts of the inducement, the redeployment cost, and uncertainty on the probability of redeployment to another well in a different field, as well as the interaction effect of the inducement and uncertainty. Accordingly, the analytical approach should involve the relative comparisons of the current well to the potential target wells for redeployment. The approach should also account for potential concerns regarding omitted variable bias, simultaneity, and reverse causality.

Therefore, several strategies are used to study the determinants of redeployment. To begin with, the analysis needs to accommodate prospective target fields, regardless of whether or not the driller redeployed a rig to a particular field. This is because the driller can redeploy a rig from the current well to many others, or none at all. Thus, dyadic measures for the explanatory variables are created for all such possible pairs, thus enabling the comparisons that drive the chosen redeployment or the lack of thereof. The main analyses employ a conditional probit model that includes firm and year fixed effects.

For additional analyses, we run a random-effects probit to address additional concerns regarding potential time-invariant omitted sources of firm heterogeneity. Finally, redeployment of rigs may be a rare event, thus potentially causing biases in the estimations. To address this concern, a penalized maximum likelihood estimation logit model (Firth, 1993) is estimated using the Stata command 'firthlogit.'

Several features of the analytical approach are also intended to preempt possible concerns regarding omitted variable bias, simultaneity and reverse causality. First, the analyses use a set of explanatory variables that are largely independent of the drillers' decisions to redeploy their rigs, thus minimizing concerns of potential correlations with the error term and associated endogeneity concerns. Specifically, it is unlikely that a given redeployment decision for one rig would affect inducements for all contractors since a commodity-based industry, like oil, is a competitive market where firms are price-takers. It is very unlikely that the movement of one drilling rig would influence oil prices, which are determined by global supply and demand considerations of this commodity-based industry. Similarly, the redeployment cost is determined by geographical distance, which is completely exogenously determined. In turn, uncertainty is driven by oil prices and well depth which are also determined independently from the particular driller. Given that these explanatory variables are largely independent of the rig redeployments, this setup should have minimal endogeneity concerns. Additionally, the explanatory variables also have a lagged temporal structure relative to the decision to redeploy, which further reduces concerns regarding simultaneity and/or reverse causality. Specifically, the construction of variables such as the inducement, redeployment costs, and uncertainty is based on data observed at least one month before the considered redeployment decision (and may reflect data from a greater lag). Thus, this temporal structure eliminates the possibility that one redeployment decision of a rig could influence the values of the explanatory variables. Also, the analyses incorporate a set of control variables related to the rig and the field, as well as fixed effects associated with year and firm to minimize omitted variable bias concerns.

Empirical results

Table 1 reports descriptive statistics and a correlation matrix associated with the full sample in the analyses. Accordingly, the summary statistics reflect information for both realized and non-realized redeployment dyads. Across all rigs in the sample, 62% (*i.e.*, 840 rigs) are redeployed at least once, while the rest do not experience redeployment anywhere and remain strictly in their home market. Within the set that are redeployed, 41% are redeployed just once (*i.e.*, 344 rigs), 28% are redeployed twice (*i.e.*, 235 rigs), 19% are redeployed three times (*i.e.*, 159 rigs), and the rest, 12% (*i.e.*, 102 rigs), are redeployed more than three times. A possible concern regarding multicollinearity is checked with inspection of variance inflation factors (VIFs). All values are at reasonable levels below 10 with a max VIF value of 3.55 and mean VIF value of 2.02. The correlation table provides preliminary support for the predictions of how the inducement, the redeployment cost, and uncertainty impact the redeployment choice. A target well site being chosen for redeployment is positively correlated with the inducement (*cf.* Hypothesis 1) and uncertainty (*cf.* Hypothesis 3). Also, such redeployment is negatively correlated with the redeployment cost (*cf.* Hypothesis 2). While the simple correlations give encouraging preliminary results, the theoretical predictions are further subjected to multivariate analyses.

****Insert Table 1 about here****

Table 2 presents multivariate models that provide evidence supporting the effects that the inducement, the redeployment cost, and uncertainty have on redeployment of rigs. Column 1 reports the baseline model with only the control variables. In Column 2, the estimated coefficient for the inducement is positive and significant (p=.006), thus corroborating Hypothesis 1. A 10% increase in the inducement for redeploying a rig from its original well site to a target well site increases the likelihood of redeployment by about 11%. In Column 3, the coefficient on the redeployment cost is negative and significant (p=.002), which is consistent with Hypothesis 2. A 10% increase in the cost of redeploying a rig from its original well site to the target well site decreases the likelihood of redeployment by about 42%. In Column 4, the coefficient on uncertainty is positive and significant (p=.004), thus providing support to Hypothesis 3. A 10% increase in uncertainty increases the likelihood of redeployment by about 30%. Column 5 shows the results for the full model with all three main predictors included and continues to support the three predictions. Finally, how the effect of inducement on redeployment is moderated by uncertainty is examined in Column 6. That column reports that the coefficient on the inducement is positive and significant (p=.001), while the coefficient on the interaction effect of the inducement and uncertainty is negative and significant (p=.018), thus supporting Hypothesis 4.

****Insert Table 2 about here****

To illustrate the interaction that is involved in Hypothesis 4, Figure 4 presents the marginal effect of the inducement along with 95% confidence intervals across various levels of uncertainty. The nonlinearity of probit models that affect interpretation of interaction effects is accommodated by following existing recommendations (Hoetker, 2007; Zelner, 2009). Figure 4 demonstrates a pattern that is entirely consistent with Hypothesis 4. Specifically, the positive marginal effect of inducement declines with the increase in uncertainty. Thus, uncertainty indeed suppresses the effect of the inducement on the odds of the rig redeployment. As described above, this happens because uncertainty makes *future* redeployment of the rig more attractive even in the presence of a *current* advantage in revenue on the alternative well over the original well.

****Insert Figure 4 about here****

Additional robustness checks

A series of additional robustness checks is run to further increase confidence in the results and interpretations. One robustness check was undertaken with regard to the constructed choice set that a firm faces. Instead of using the full choice set, alternative sets of counterfactual observations were generated and used in the analyses. In particular, different subsets of unrealized dyads were randomly picked from the original full choice set, thus reducing the choice set for a given rig. Specifically, for each realized dyad of a given rig, 50 unrealized dyads of potential unselected targets were randomly used. This exercise was also repeated with 30 unrealized dyads. With these different random subsamples, results very similar to those reported here were obtained. These supplementary results are reported in Table 3 where Columns 2 and 4 focus on the full model specification for these randomly picked unrealized dyads of 50 and 30, respectively.

****Insert Table 3 about here****

In addition, for each chosen alternative well, a matched sample of unchosen wells with characteristics similar to the selected well was created (matched by their size, complexity, and type of crude oil produced). This matching approach better accommodates systematic differences between the selected well and potential non-selected target wells. If any systematic differences existed between the selected and these other target wells, then potential confounding factors could interfere with the diagnosis of the effects of the inducement, of the redeployment cost, and of uncertainty on redeployment. Specifically, a coarsened exact matching (CEM) technique was used to find an appropriate unselected target well for each selected target well. Using such a matching technique essentially preprocesses the full choice sample by keeping those unrealized target wells that match and pruning, or dropping from the sample, those unrealized target wells that do not match. As a result of matching, the new sample consists of the 108,281 observations that were realized redeployment dyads (*i.e.*, unchanged from the original sample) and 526,461 unrealized dyads (*i.e.*, pruned from 1,972,391 in the original sample). The remaining data have better 'balance' between the two groups—the improvement in the data after CEM is typically less model dependence, lower bias, and increased efficiency (Iacus, King, & Porro, 2012; King & Zeng, 2006). Using the retained matched data sample, the CEM approach enables the main parametric estimation model of choice, which for the present analysis is rerunning the conditional probit model. As Column 6 in Table 3 shows for the full model specification, all the four hypotheses continue to be corroborated using CEM.

Finally, the predictions were tested using a random-effects probit model to further account for focal firm omitted heterogeneity; the results of these estimations are similar to the reported above. Given that many dyads do not involve redeployment, another concern is the possibility that rare events could cause biases in the estimations. Binary models, such as probit, can suffer from small-sample bias in their maximum likelihood estimation. While this bias can emerge from a small absolute number of events, which does not apply in our sample, to mitigate such concerns, a penalized maximum likelihood logit model was estimated following Firth (1993) and using the Stata command 'firthlogit.' The reported results remain robust (results available from the authors upon request).

DISCUSSION

Contributions and implications

Resource redeployment is an important and popular resource-allocation strategy that involves the withdrawal of various resources from their original use combined with their allocation to another use. This strategy was introduced to management research by Anand and Singh (1997). Since then, the phenomenon has been intensely examined both theoretically and empirically, and it has even been featured as a new justification for the performance of diversified, or multi-business, firms.[7] With this increasing appeal to resource redeployment in management research, this study attempts to resolve two challenges that have persisted in this literature. The first challenge is that resource redeployment was used to study multi-business firms alone, even though it is also available to single-business firms. The second, related challenge is that resource redeployment has been notoriously hard to capture empirically. Accordingly, existing empirical operationalizations were at best consistent with resource redeployment, but potentially captured other resource allocation strategies, thus casting doubt on the extent to which resource redeployment is actually used by firms and on its antecedents.

[7] The annual rate of referring to resource redeployment explicitly (*i.e.*, excluding cases where it was meant but was named differently) in publications in *Organization Science*, *Strategic Management Journal*, *Academy of Management Journal*, *Academy of Management Review*, *Management Science*, *Administrative Science Quarterly*, *Strategy Science*, *Journal of Management*, *Strategic Management Review*, *Journal of International Business Studies*, *Managerial and Decision Economics*, *Strategic Entrepreneurship Journal*, *Journal of Economic Behavior and Organization*, *Industrial and Corporate Change*, *Journal of Business Venturing*, and *Journal of Management Studies* has grown from 11 in 1997 to 44 in 2021.

Therefore, this study theoretically examines resource redeployment in single-business firms, and then empirically demonstrates resource redeployment and its determinants. To elaborate resource redeployment theoretically, this study adapts previous formal models of redeployment in multi-business firms to the context where a single-business firm can redeploy its resources from their current use to a new use. The model demonstrates that such redeployment is monotonically positively affected by the inducement, which is the current performance advantage of the new use over the original use, and by uncertainty in that performance. Resource redeployment is also shown to be monotonically negatively affected by the redeployment cost. In addition to these direct effects, uncertainty negatively moderates the positive effect of the inducement on redeployment. To empirically demonstrate resource redeployment and to test the four predictions in the context of single-business firms, this study develops a dataset that involves all oil wells drilled in Texas over twelve years. The to-be-redeployed resource in this context is the rig that is possessed by a single business firm, an oil-drilling contractor. The contractor can continue to use its rig in the current field or can withdraw the rig from that field and reallocate that rig to another field. The inducement, in this case, is captured by the revenue on the drilling contracts in each field, and the redeployment cost is operationalized as the geographical distance at which the rig needs to be transported to the new field. The empirical tests robustly confirm the four predictions derived with the formal model. Furthermore, in the empirical analysis all the effects are shown to be economically meaningful.

The chief contribution of this study is that it appears to be the first to unambiguously measure redeployment of non-financial resources, which cannot be confused with other resource allocation strategies. Each rig that this study regards as redeployed by an oil drilling contractor to another field is known to have been actually dismantled from the original well, to have been physically moved to a different field, and to have been reassembled on another well. This precise measure of resource redeployment ensures not only that the revealed extent of resource redeployment is credible but also that the diagnosed relationships between such redeployment and its determinants are reliable. In addition, the unique combination of formal theorizing and empirical analysis provides a compelling elaboration and corroboration of the theory of resource redeployment. By reliably detecting redeployment of non-financial resources, this study also goes beyond the context of redeployment of financial capital, which has been considered in research on internal capital markets (Gertner, Scharfstein, and Stein, 1994).

For future research that seeks to study resource redeployment in single-business firms, it might build upon our study in one of several ways. To begin with, it would be valuable to build up a taxonomy of resource redeployment in these contexts. Whereas resource redeployment across businesses in diversified firms is conceptually clear in the existing literature (Helfat and Eisenhardt, 2004; Sakhartov and Folta, 2015), for single-business firms research might elaborate upon the contexts across which firms are redeploying resources. While we consider the case of geographic locations of oil-drilling rigs, resource redeployment might also occur across generations of products or technologies. Resource redeployment might also happen across organizational units or teams, or it might be defined in associated product market terms (*e.g.*, across distribution channels, customer segments, *etc.*). An advantage of our research design is that we can focus on tangible resources (*i.e.*, oil drilling rigs), and future research might elaborate upon the redeployment of financial capital and various forms of tangible and intangible resources that firms redeploy.

Limitations and future research directions

The advantages of the unique dataset and empirical design in this study also present some natural limitations that future research might address. To begin with, it would be valuable to study resource redeployment in single-business firms situated in other industrial contexts to examine further the roles played by inducements, redeployment costs, and uncertainty. In the setting of this study, oil prices play an important role in shaping the uncertainty surrounding the exercise of the redeployment option, but in other contexts it might be that exchange rates or various local demand or supply conditions figure more prominently in such choices, for instance. The present study is focused on the oil-drilling industry in Texas, and it would be valuable to examine such decisions across borders, or to examine how firms make redeployment decisions in very different sectors (*e.g.*, service businesses, tech, *etc*.).

While the empirical design in this study isolates redeployment as a resource allocation strategy, future research might also examine other ways in which firms can leverage their resources. These might include boundary of the firm choices such as acquisitions as well as divestitures, among others. Each of these resource allocation choices involves its own advantages and potential demerits, so it would be valuable to analyze resource redeployment from a comparative perspective that accommodates other means of growth and ways of leveraging the firm's tangible and intangible resources.

Because this study has focused on the antecedents of resource redeployment and not its consequences, the study is also ultimately silent on the performance implications of resource redeployment. For example, it would be interesting and valuable to determine whether and when single-business firms derive competitive advantages from their resource redeployment activities, and whether these advantages are unique compared to other means of leveraging or reallocating resources (*e.g*., expanding into a new industry through M&A). Future research could examine the implications of resource redeployment not only for firm profitability, but also for other intermediate outcomes such as innovation and growth.

In studying resource redeployment, the present study has relied on secondary data with all benefits and limitations that such data entail. Primary data would let scholars gather insights into new questions, such as whether and when firms consider resource redeployment compared to other resource allocation strategies. Such work could also explore more specific topics such as the potential sets of resource uses that executives consider during decision making and the potential heuristics they draw upon when making resource reallocation decisions. Survey research has proven fruitful on resource redeployment in the context of horizontal acquisitions (Capron, Dussauge, and Mitchell, 1998), and this research method also holds promise for studying resource redeployment in other contexts, including for single-business firms.

Many of the identified research directions apply to resource redeployment in multi-business firms in the realm of corporate strategy; but this study also emphasizes that existing empirical research on resource redeployment has focused solely on multi-business firms, so it would be especially valuable to extend this research in new ways to single-business firms. The present study calls for such research with the recognition that data challenges exist for diagnosing resource redeployment in firms, but the study also highlights there are many exciting opportunities to enrich the theory in this new context. Such advances promise to connect ideas surrounding resource redeployment with the competitive strategy literature and new research streams outside of corporate strategy as the traditional domain of resource deployment research. It is hoped that this study encourages new empirical research on resource redeployment and that this research agenda might devote attention to single business firms in the coming years.

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Table 1. Correlations and summary statistics

	1	2	3	4	5	6	7	8	9	10	11
1. *Redeployed*	1										
2. *Inducement*	0.09	1									
3. *Redeployment cost*	-0.06	-0.01	1								
4. *Uncertainty*	0.08	0.00	0.o1	1							
5. *Focal well complexity*	0.03	0.03	0.17	0.00	1						
6. *Target well complexity*	-0.02	-0.01	-0.01	0.00	0.00	1					
7. *Rig field experience*	-0.01	-0.00	0.00	0.01	0.00	-0.01	1				
8. *Rig performance*	-0.01	-0.02	-0.00	0.00	-0.25	0.00	0.13	1			
9. *Rig profit*	-0.03	-0.03	-0.02	0.02	-0.04	0.01	0.20	0.16	1		
10. *Focal competitive density*	0.01	0.01	0.01	0.00	-0.03	0.00	-0.01	0.04	-0.23	1	
11. *Target competitive density*	-0.03	-0.05	0.00	0.01	0.00	0.05	-0.02	0.00	0.02	-0.01	1
VIF (mean VIF = 2.019)	1.38	1.76	1.89	1.54	3.55	2.32	1.61	1.29	1.82	2.56	2.49
Mean	0.0136	1.190	218.4	0.502	2.001	1.905	54.12	0.499	17.49	13.05	14.50
S.D.	0.116	1.465	96.58	0.29	0.819	0.786	31.45	3.751	29.4	7.768	8.652

Table 2. Estimation of the likelihood of redeployment

Conditional Probit Model	DV: *Redeployed*											
	(1)		(2)		(3)		(4)		(5)		(6)	
Constant	-2.599	*(.036)*	-2.228	*(.031)*	-2.406	*(.033)*	-2.195	*(.030)*	-2.063	*(.027)*	-2.094	*(.034)*
	(1.240)		(1.025)		(1.127)		(1.014)		(.931)		(.981)	
Target competitive density	-0.0024	*(.531)*	-0.0023	*(.517)*	-0.0022	*(.524)*	-0.0019	*(.519)*	-0.0020	*(.509)*	-0.0018	*(.506)*
	(.0038)		(.0032)		(.0034)		(.0031)		(.0028)		(.0028)	
Focal competitive density	0.0042	*(.349)*	0.0033	*(.332)*	0.0037	*(.341)*	0.0033	*(.335)*	0.0031	*(.324)*	0.0029	*(.329)*
	(.0045)		(.0034)		(.0039)		(.0034)		(.00302)		(.00302)	
Rig profit	-0.0025	*(.028)*	-0.0022	*(.037)*	-0.0021	*(.032)*	-0.0018	*(.038)*	-0.0016	*(.042)*	-0.0015	*(.058)*
	(.0012)		(.0012)		(.0011)		(.0009)		(.0008)		(.0008)	
Rig performance	-0.0043	*(.624)*	-0.0036	*(.612)*	-0.0039	*(.618)*	-0.0035	*(.614)*	-0.0032	*(.605)*	-0.0031	*(.620)*
	(.0088)		(.0007)		(.0078)		(.0069)		(.0062)		(.0063)	
Rig field experience	-0.00310	*(.003)*	-0.00234	*(.005)*	-0.00271	*(.004)*	-0.00231	*(.005)*	-0.00204	*(.006)*	-0.00203	*(.007)*
	(.0001)		(.0008)		(.0009)		(.0008)		(.0007)		(.0007)	
Target well complexity	-0.0080	*(.058)*	-0.0064	*(.046)*	-0.0071	*(.052)*	-0.0063	*(.047)*	-0.0057	*(.040)*	-0.0056	*(.050)*
	(.0042)		(.0034)		(.0040)		(.0032)		(.0033)		(.0034)	
Focal well complexity	0.0083	*(.033)*	0.0071	*(.022)*	0.0077	*(.027)*	0.0072	*(.023)*	0.0066	*(.017)*	0.0065	*(.024)*
	(.0039)		(.0031)		(.0035)		(.0032)		(.0028)		(.0029)	
Inducement			0.0124	*(.006)*					0.0116	*(.001)*	0.0113	*(.001)*
			(.0045)						(.00362)		(.00343)	
Redeployment cost					-0.0026	*(.002)*			-0.0015	*(.004)*	-0.0014	*(.007)*
					(.0008)				(.0005)		(.0005)	
Uncertainty							0.0814	*(.004)*	0.0774	*(.005)*	0.0536	*(.009)*
							(.0282)		(.0275)		(.0205)	
Inducement*Uncertainty											-0.0383	*(.018)*
											(.0161)	
Firm FE	Yes		Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Log-likelihood	-147,889		-147,769		-146,119		-146,105		-146,078		-146,057	
Pseudo R-squared	0.0120		0.0125		0.0236		0.0231		0.0238		0.0240	
N	2,080,672		2,080,672		2,080,672		2,080,672		2,080,672		2,080,672	

Note: The standard errors are reported in parentheses below each coefficient. The *p*-values are reported in parentheses to the right of each coefficient.

Table 3. Supplementary analyses estimating the likelihood of redeployment

Conditional Probit Model	DV: Redeploy											
	sample of randomly picked 50 unrealized dyads				sample of randomly picked 30 unrealized dyads				CEM matched sample			
	Model 1: controls only		**Model 2**: full model		**Model 3**: controls only		**Model 4**: full model		**Model 5**: controls only		**Model 6**: full model	
Constant	-2.807	*(.041)*	-2.751	*(.042)*	-2.209	*(.031)*	-2.165	*(.033)*	-1.559	*(.120)*	-1.528	*(.124)*
	(1.364)		(1.350)		(1.024)		(1.015)		(1.004)		(.994)	
Target Rival Density	-0.00274	*(.521)*	-0.00266	*(.525)*	-0.00291	*(.510)*	-0.00282	*(.515)*	-0.00405	*(.409)*	-0.00393	*(.413)*
	(.00426)		(.00418)		(.00442)		(.00433)		(.0049)		(.00481)	
Focal Rival Density	0.00485	*(.341)*	0.0048	*(.369)*	0.00494	*(.365)*	0.00489	*(.393)*	0.00664	*(.282)*	0.00657	*(.310)*
	(.00509)		(.00535)		(.00545)		(.00572)		(.00617)		(.00647)	
Rig Profitability	-0.00291	*(.020)*	-0.00284	*(.022)*	-0.00191	*(.065)*	-0.00185	*(.061)*	-0.00356	*(.016)*	-0.00349	*(.017)*
	(.00125)		(.00124)		(.00103)		(.00099)		(.00148)		(.00147)	
Rig Performance	-0.00494	*(.528)*	-0.00484	*(.531)*	-0.00387	*(.549)*	-0.00379	*(.553)*	-0.00623	*(.488)*	-0.00611	*(.490)*
	(.00783)		(.00773)		(.00646)		(.00639)		(.00898)		(.00884)	
Rig Experience Field	-0.00357	*(.002)*	-0.00346	*(.003)*	-0.00366	*(.029)*	-0.00355	*(.039)*	-0.00485	*(.008)*	-0.0047	*(.010)*
	(.00117)		(.00116)		(.00167)		(.00172)		(.00183)		(.00181)	
Target Well Complexity	-0.0094	*(.052)*	-0.0093	*(.054)*	-0.0071	*(.079)*	-0.0069	*(.082)*	-0.0087	*(.069)*	-0.0085	*(.072)*
	(.0049)		(.0048)		(.0041)		(.0043)		(.0048)		(.0047)	
Focal Well Complexity	0.0093	*(.038)*	0.0091	*(.040)*	0.0077	*(.055)*	0.0074	*(.063)*	0.0043	*(.082)*	0.0042	*(.085)*
	(.0046)		(.0045)		(.0042)		(.0041)		(.0025)		(.0024)	
Predictors:												
Inducement			0.02396	*(.019)*			0.00904	*(.008)*			0.0193	*(.016)*
			(.01022)				(.00342)				(.00803)	
Switching Cost			-0.00313	*(.007)*			-0.00123	*(.003)*			-0.00144	*(.011)*
			(.00116)				(.00042)				(.00057)	
Uncertainty			0.1092	*(.021)*			0.2047	*(.015)*			0.1365	*(.009)*
			(.0472)				(.0839)				(.0524)	
Inducement*Uncertainty			-0.0601	*(.001)*			-0.0712	*(.018)*			-0.0383	*(.023)*
			(.0186)				(.0301)				(.0169)	
Log-likelihood	-162,631		-158,348		-181,541		-177,692		-131,817		-125,726	
Pseudo R-squared	0.0131		0.0133		0.0082		0.0085		0.0251		0.0259	
N	1,268,522		1,268,522		852,863		852,863		634,742		634,742	

Note: The standard errors are reported in parentheses below each coefficient. The *p*-values are reported in parentheses to the right of each coefficient.

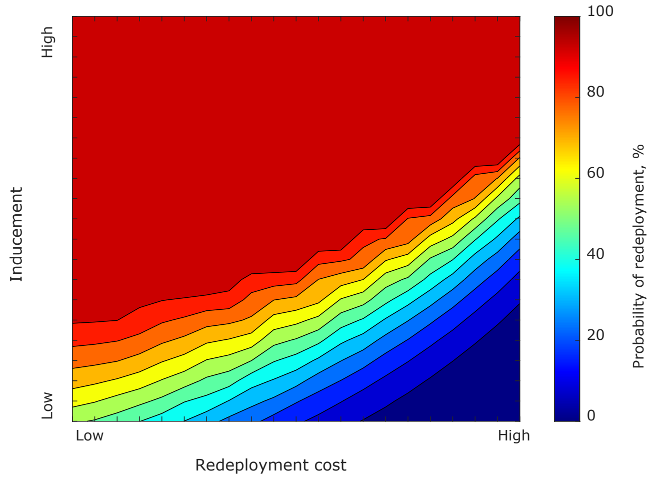


Figure 1. Implications of inducement and redeployment cost for rig redeployment

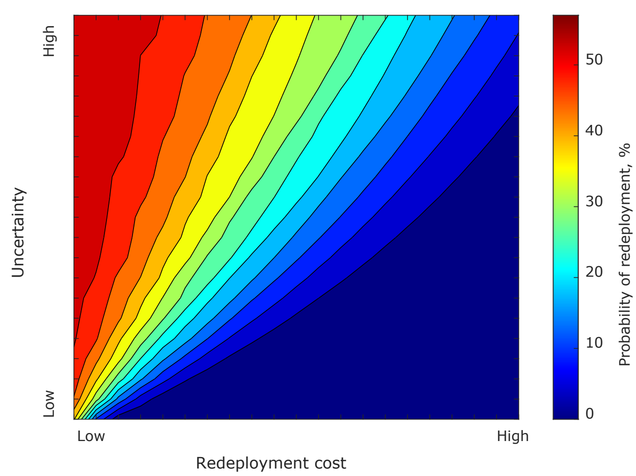
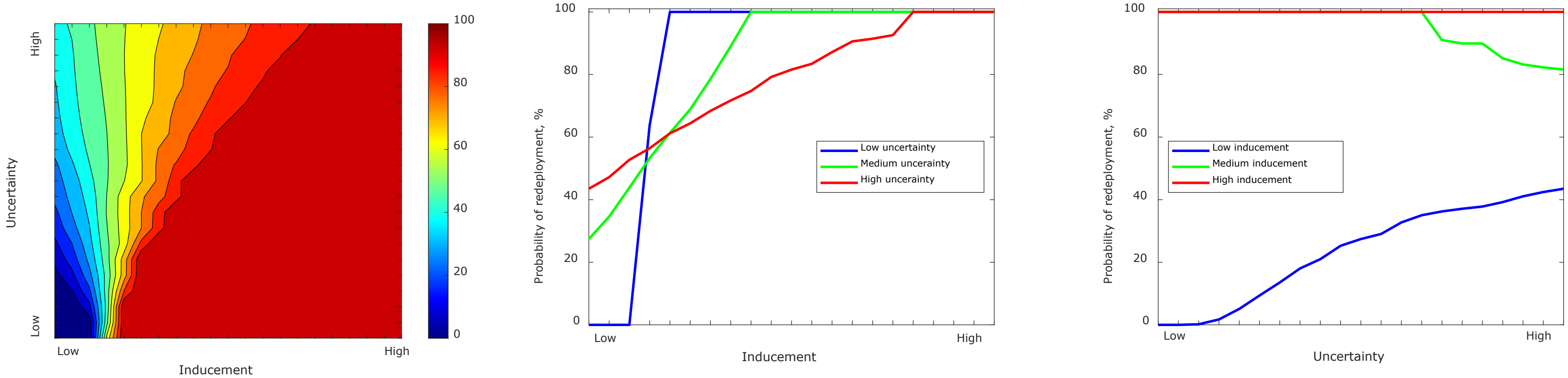


Figure 2. Implications of uncertainty and redeployment cost for rig redeployment



A. Effect of uncertainty on rig redeployment for various levels of inducement

B. Effect of inducement on rig redeployment for three levels of uncertainty

C. Effect of uncertainty on rig redeployment for three levels of inducement

Figure 3. Implications of uncertainty and inducement for rig redeployment

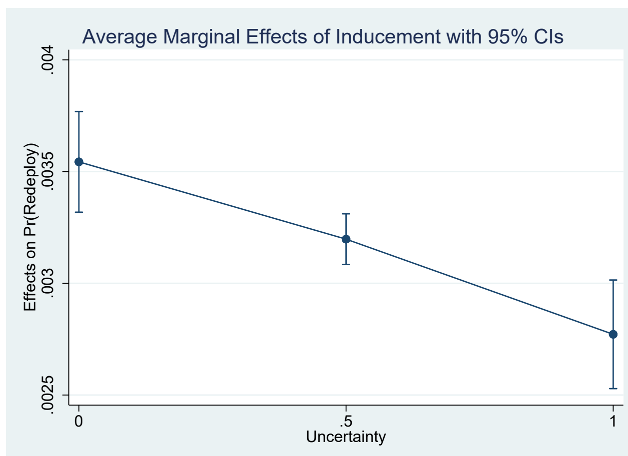


Figure 4. Marginal effects of inducement for three levels of uncertainty