Reactivation of idled resources in uncertain environments:

The role of firm capabilities

ABSTRACT

How does industry uncertainty influence the decision to reactivate idled resources? While existing theory suggests that uncertainty increases the value of waiting and that external factors, such as competitive moves, erode the value of deferring investment, we argue that internal conditions related to a firm's capabilities are an unacknowledged source of heterogeneity in reactivations. We posit that extended idleness can lead to an erosion of *operational capabilities* and increase the cost of returning the resource to an active state. This effect reduces the value of delaying reactivation when there is demand uncertainty. By contrast, we argue that a firm's *reactivation experience* enhances the waiting option under uncertainty as it enables the firm to maintain preferential access over time and preserve the option to invest. Examining decisions to reactivate idled rigs of oil and gas drilling firms in Texas, we find that firms with superior operational capabilities are more likely to reactivate resources under demand uncertainty and that a firm's reactivation experience increases the likelihood of delay reactivations. Our findings shed new light on the role of different organizational capabilities (i.e., lower and higher-order capabilities) in the trade-off between commitment and flexibility when making resource allocation decisions under uncertainty.

Keywords: *real options theory, resource-based perspectives, capabilities, resource reactivation, uncertainty*

Introduction

Resource reactivation is an important process in managing a firm’s resources. After a period of idleness, firms reactivate dormant or unused productive resources (e.g., plant, equipment, workers) to exploit business opportunities and facilitate growth (Hutt, 1939; Penrose, 1959). Strategy research has linked reactivation to various decisions, such as capacity expansions (Corts, 2008), commercialization of shelved technologies (Garud & Nayyar, 1994), knowledge inventory management (Levitt & March, 1988; Miller, 2002), and reentry (Ghemawat, 1991). As reversing the temporary idling of resources can be costly (Dixit, 1992; Moel & Tufano, 2002), and because managers have some discretion for future reactivation of idled resources, industry uncertainty is likely to influence the timing of resource reactivations. However, though the management of a firm’s resources is influenced by the environmental context (Penrose, 1959; Sirmon, Ireland, & Hitt, 2007), empirical insights on the role of uncertainty in the environment for decisions to reactivate idled resources are missing. Therefore, we ask the question: *How does industry uncertainty influence the decision to reactivate idled resources?*

Existing theory is limited in answering our research question for at least two reasons. First, resource-based perspectives have traditionally assumed that idle resources should be avoided (Penrose, 1959) and unused resources should be divested or redeployed (Sirmon et al., 2007; Chang & Matsumoto, 2021). However, remaining idle does not necessarily imply inefficiency or something to be avoided (Hutt, 1939: xi, 16; Winston, 1974). Firms seem to rather respond differently with their idling and reactivation decisions, even under similar environmental conditions. For instance, while some firms within industries reactivated quickly after the Covid-19 crisis, others waited and deferred the decision to reactivate (e.g., *WSJ*, 2022).

However, resource-based perspectives say little about how environmental uncertainty shapes a firm's idiosyncratic value of deferring resource reactivations.

Second, while real options theory provides valuable insights into the role of uncertainty for entry decisions (Lieberman, Lee, & Folta, 2017; Folta & O'Brien, 2004), reactivating resources and exercising the option to restart after an idle period is distinct from entry (Dixit & Pindyck, 1994). Decisions to commit versus defer reactivation may be different because firms face *reactivation costs* that depend on their capabilities, as these can erode during idling (Helfat & Peteraf, 2003; Ross, Li, Hawk, & Reuer, 2023) but can also grant privileged access to future states and enhance the ability to wait (Garud & Nayyar, 1994; Barnett, 2008: 618). However, the real options theory on reactivation decisions falls short in incorporating those "organizational realities", offering limited utility for strategy (Trigeorgis & Reuer, 2017).

We seek to address these research gaps by integrating real options theory with resource-based perspectives to explore the role of firm capabilities in decisions to reactivate resources under uncertainty. We posit that the *reversibility* of initial idling decisions is contingent on a firm's organizational capabilities and that intertemporal interdependencies (Ghemawat, 1991; Leiblein, Reuer, & Zenger, 2018) in the timing of reactivation under uncertainty are shaped through two mechanisms: First, firms with superior *operating capabilities* face a reduced option value to wait when facing demand uncertainty as they are more concerned about capability erosion from extended idling, which could increase the irreversibility of switching back to an active mode (i.e., *time-dependent sunk cost*) and, thus, provides an incentive to reactivate. Second, firms with better *reactivation capabilities* are more likely to preserve option value over time and access alternative states at lower cost (i.e., *preservation of option value*) as they have learned to reactivate efficiently through experience from prior idling-reactivations cycles and developed organizational routines over time.[1] Consequently, a firm's reactivation experience motivates firms to delay resource reactivation when facing uncertainty.

Using a dataset of Texas oil drillers who idled and reactivated drilling rigs between 2010 and 2022, we find support for our arguments. We find that demand uncertainty reduces the likelihood of reactivation. We then provide evidence that this effect is reduced for firms with superior capabilities and enhanced for firms with high reactivation experience. These findings have important empirical and theoretical contributions: First, we link early work on idle resources (Hutt, 1939) with the modern resource-based perspective in strategy and integrate the real options perspective to explain how environmental uncertainty shapes the *timing* of resource reactivations. Our insights enhance resource management processes (Sirmon et al., 2007; Karadag & Poppo, 2021) and shed light on how a firm's capabilities and their impact on the reversibility of the state of idleness determine heterogeneity in resource allocations and investment when facing uncertainty. These insights complement prior literature that views resource allocation through a resource and capability lens (Maritan & Lee, 2017). Second, by providing insights into how *internal* factors determine the "zone of inaction" under uncertainty (i.e., hysteresis), we complement research that has largely focused on how external factors (i.e., competition, market growth) erode the value of waiting (e.g., McGrath, 1997). By revealing how organizational capabilities influence the "intertemporal trade-off of present risk v. future risk" (Dixit, 1992: 110) in the uncertainty-investment relationship, we enhance our understanding of the trade-off between commitment and waiting (Ghemawat, 1991; Leiblein et al., 2018).

[1] We define a "resource" as an asset or input to production, a "capability" as a firm's ability to perform a set of tasks in routine activity (Helfat & Peteraf, 2003; Helfat & Winter, 2011), and capability erosion a the "systemic loss of effective capabilities already established in an organization" (Rahmandad & Repenning, 2016: 651). While "operating capabilities" are ordinary capabilities (Winter, 2003), we characterize "reactivation capabilities" as a higher-order capability that links to a firm's "dynamic capability to [speedily and reliably] scale up" (Knudsen, Levinthal, & Winter, 2014: 1582).

BACKGROUND LITERATURE

Reactivation of idled resources

In "*The Theory of Idle Resources*" (Hutt, 1939[1977]) it is argued that resources are at the disposal of the firm and that resources that still have capital value can be temporarily valueless when they have no scrap value or immediate hire value. Hutt emphasizes that the value is an estimate of the decision-maker that changes with fluctuating demand. While traditional economics (Marshallian rules) would assume to reactivate when the net present value (NPV) of operations is equal to or above zero, real options theory would consider the flexibility value of holding the option to reactivate when facing uncertain industry conditions (e.g., Trigeorgis, 1996). Thus, even when the NPV is positive it may be beneficial to remain shut. This "rational inertia" does not require risk-averse investors or uncertainty avoidance (e.g., Cyert & March, 1963), but is the result of a combination of three aspects: uncertainty about the environmental conditions, managerial discretion to delay (i.e., the investment opportunity does not disappear when not immediately taken), and sunk costs (irreversibility) that occur if the action is reversed in the future (Dixit, 1992: 108).

Seminal works in economics, finance, and operations have studied idling and reactivation decisions as flexible capacity choices in options to temporarily alter the scale of operations (e.g., Dixit & Pindyck, 1994; Pindyck, 1988; Trigeorgis, 1996). Conceptually, the presence of switching costs when switching back and forth between operating modes creates a "compoundness effect" in the option to temporarily suspend operations and restart (Trigeorgis, 1994: 187; Dixit & Pindyck, 1994: 244). Firms that have exercised the first stage option, then acquire the subsequent option to reactivate. The general structure of such a decision can be found, for instance, in decisions to reactivate shelved developed technologies prior to their commercialization (Garud & Nayyar, 1994), switch technologies over time (Miller, 2002), reenter after past exit (O'Brien & Folta, 2009; Lieberman et al., 2017), and to shift production between countries (Kogut & Kulatilaka, 1994). In the absence of switching costs, the option value is simply the sum of both options. However, exercising the first stage creates vulnerabilities to a firm's resources and capabilities and thus creates interdependencies between options as this decision influences the second stage. Those interdependencies make decisions strategic and deserve attention from strategy researchers (Leiblein et al., 2018). Furthermore, path dependencies will likely shape the variants a firm can select from. The value of these alternative options depends on the existing state of the organization, such as a firm's existing position and capabilities (Levinthal, 2021: 29).

While traditionally real options research assumed that holding and exercising options is without longer-term organizational consequences and that suspension decisions are at least partially reversible, more recently, management research has raised concerns about the erosion of assets when suspending operations (Brown, Carpenter, & Petersen, 2019; Ross et al., 2023). These insights implicitly complement the view that investments in physical assets are interlinked with capabilities and other intangible assets (Baldwin & Clark, 1992: 68; Maritan, 2001: 513) as a lack of investments (due to resource idling) can equally shape a firm's assets (due to erosion). In the context of temporary suspensions and resource idling, however, we lack insights about the role of a firm's capabilities in decisions to reverse the state of idleness and reactivate idled resources or, alternatively, to wait and keep the second stage option open. Garud and colleagues (1998) critically commented that organizational capabilities should be incorporated when estimating the value of keeping an option open. They point out that attention to organizational factors would make the real options perspective more useful when comparing firms' resource allocation and investment decisions under uncertainty.

Organizational capabilities and the timing of reactivation under uncertainty

When facing uncertainty, the decision to reactivate is guided by the choice between undertaking an investment now versus remaining flexible by delaying investment commitment. Since there is uncertainty, there can be value in waiting because time can bring more information, and the later decision can be a better one. Avoiding an action in uncertain environments that could turn out to be wrong in the shorter term creates an incentive to wait as downside risks can be avoided while upsides remain. Dixit (1992: 118) refers to the "trade-off between current and future risk" and points out that due to sunk costs, it may not be worth taking a less perfect action now and reversing it later because sunk costs cannot be recouped (p. 108).

These considerations are central to understanding the intertemporal influence of resource allocation and investment decisions under uncertainty (e.g., Ghemawat & Del Sol, 1998; Leiblein et al., 2018). One may ask, why do we need a fresh look at this topic? What is conceptually different about resource reactivations, compared to common views on the timing of investments under uncertainty, such as entry? Reactivating an idle resource implies that the resource had been deployed before, and reactivating *reverses* the state of idleness. This reversal is conceptually different from the "irreversibility" of an investment project typically considered in waiting options (e.g., McDonald & Siegel, 1986). Both are relevant for resource reactivation decisions, but existing insights in strategy have largely looked at the latter and not the former (with few exceptions: Moel & Tufano, 2002; Corts, 2008). Timing decisions can be strategic and distinct because the state of idleness can erode the capabilities required to efficiently leverage the resource once activated.

Such effect could occur when firms seek to reduce capital expenses by shutting down operations and temporarily idling their resources (e.g., plants, equipment, workers) in economic downturns (Argote, 1990; Benkard, 2000; Thompson, 2007). Thus, the *reversal* of the idling mode can be challenging. After periods of reduced investments for maintenance and layoffs during idling, firms struggle when trying to reactivate idled resources. After lifting COVID-19 restrictions and travel bans, for instance, many organizations struggled to reactivate operations and recover their (pre-pandemic) operating efficiency levels despite the recovery of demand (e.g., London Heathrow airport; *WSJ*, 2022). Because of the difficulty of "reactivating dormant factors, reacquiring abandoned ones or, more generally, recreating lapsed opportunities to deploy particular factors" (Ghemawat, 1991: 21), in extreme cases firms can be bound to persist with their initial strategy and face continued idleness. The strategy literature has underexplored the notion that commitment can also occur from *not investing* and the possibility of foreclosing future decisions (Ghemawat, 1991) and how forward-looking decision-makers avert such possibilities.

Some research has emphasized the "timing" of activities to maintain and avoid erosion could become critical here (e.g., Karadag & Poppo, 2021). For example (time delays increase erosion (R&R paper). Just like some firms stay out there and remaining active even in challenging times can be a motive to maintain capabilities (Ross et al., 2023). Later reactivation of idled resources can increase the "difficulty of recalling discarded opportunities on the original terms" (Ghemawat, 1991: 20). Early work on real options has argued that the cost of reactivation and switching back to an active mode may be time-dependent (Dixit & Pindyck, 1994), but not explicated the organizational drivers that determine such sunk cost. The resource-based perspective can help explicate the organizational cost of continued idleness. As resource idling can enhance resource vulnerabilities (Ross et al., 2022) that increase under uncertainty (Le-Breton-

Miller & Miller, 2016), resource erosion dynamics during idling can enhance the irreversibility of the initial shut-down decision and increase the likelihood of delay in reactivating idled resources. Forward-looking decision-makers consider the intertemporal impact on the sunk cost (or irreversibility) to reactivate now versus later. Real options literature has also argued that managers have expectations about exogenous and endogenous parameters influencing such decisions (Dixit & Pindyck, 2000). We will argue that such expectations will depend on a firm's capabilities. Overall, we thus provide firm-specific contingencies related to capabilities influencing the flexibility value (wait to invest) under uncertainty in the context of reactivation of idled resources.

HYPOTHESES DEVELOPMENT

Greater uncertainty causes firms to delay switching between operating modes for the following reasons. Uncertainty widens the distribution of possible future economic conditions, such that the market demand could either turn stronger or weaker. Uncertainty also manifest how quickly current conditions can change. Even as firms are in the midst of an expansionary or contractionary situation, they face uncertainty about whether such trends are merely temporary or sustainable. Thus, when managing resources in uncertain environments, the firm's future potential of resources to create and capture value is difficult to evaluate (Sirmon et al., 2007). Uncertainty in volatile environments is not only whether the market is recovering, but also how long it will take to recover and to what extent it will recover (Mascarenhas & Aaker, 1989; Bloom, 2014; 2018; Pindyck, 1999; 2001). For instance, as oil prices were rebounding in 2013, oil companies continued to hesitate to restart investments and production until the following year.

As a result, firms under uncertainty hesitate to commit because market conditions can turn worse or new information arises that affects desirability. Then, these firms that jumped in to invest can regret that decision due to incurring the cost of entry and also possibly the cost to reverse that decision. Thus, the option to defer increases with uncertainty due to the value of keeping strategic flexibility, especially when the investment is sufficiently costly to reverse (Pindyck, 1988). Such forward-looking perspective has been adopted in prior empirical studies on entry decisions that consider cost that are sunk or irrecoverable upon (future) exit (Lieberman, Lee, & Folta, 2017).

Uncertainty causes firms to keep those operations idled until conditions improve. Suppose the firm is currently in an idling state. In that case, the decision to reactive must consider adjustment costs to restart operations (Ghemawat, 1991) as well as the cost to idle again should market conditions become worse (Dixit & Pindyck, 2000). Restarting operations requires not only refurbishing rusty equipment but also search costs of rehiring and retraining previously furloughed employees. Thus, even if market conditions begin improving and NPV may be positive, the firm keeping operations idled can be rational because such decision can keep open the option on future revenues, while truncating the downside outcome due to uncertainty. Such delayed action of doing nothing under uncertainty is consistent with real options reasoning of rational delay, or the "hysteresis effect" (Dixit, 1992). Thus, overall, we predict a positive effect of uncertainty enhances the value of the option to reactivate and the likelihood of delayed reactivation.

Hypothesis 1: Uncertainty will decrease the likelihood of resource reactivation.

The Role of Operational Capabilities in Reactivation Decision under Uncertainty

One source of firm heterogeneity in reactivation decisions after idling relates to a firm's organizational capabilities. Strategy scholars have suggested the important role that capabilities can play in a firm's investment decisions (Sirmon et al., 2007; Stadler, Helfat, & Verona, 2013), and have attempted to shed light on firm behavior under uncertainty by linking the resource-based view and real options, such as explaining how heterogeneity in accessing and exercising particular investment options during changing environmental conditions can be a function of their differential capabilities (e.g., Trigeorgis & Reuer, 2017). Yet these previous works have given the most attention to firm growth and expansion choices. We intend to complement this research and provide a new basis for joining dynamic RBV and real options by theorizing the role of capabilities – specifically concerns about their erosion - on firms' resource reactivation decision after idling.

Building on the above hypothesis arguing that a firm under uncertainty can remain idled until uncertainty resolves before jumping back into the market (i.e., reactivating), keeping operations temporarily suspended during this period, however, is not costless. Among the costs of idling is the erosion of the firm's capabilities. Maintaining capabilities requires a consistent flow of investment to continually replenish the underlying resources and assets, and the consistent exercising by workers of their routines and skills that comprise of capabilities (Dierickx & Cool, 1989; Grant, 1991; Maritan, 2001). Interruptions to such maintenance and exercising of capabilities – for instance, due to the degradation of not only the physical machines and equipment being idled - results in their erosion (e.g., Dierickx & Cool, 1989; Le Breton-Miller & Miller, 2015). More importantly, the associated workers on idled projects can forget their routines and skills, which can hinder their ability to efficiently execute tasks (Benkard, 2000; Brett & Millheim, 1986; Thompson, 2007). In particular, the longer workers are furloughed from their jobs, the more severe their knowledge deteriorates and the more expensive the additional investments needed to retrain them and refresh organizational routines (Garud & Nayyar, 1994; Miller, 2002). Such fragility of a capability advantage in uncertain environments has an asymmetric effect: the advantage is resource-intensive to develop, but quick to destroy and hard to resuscitate (Le Breton-Miller & Miller, 2015).

Superior capabilities are especially prone to erosion. They are built on advanced and complex routines and knowledge, and hence are inherently more fragile to the disruptions to employees' workflows described above when workers are furloughed or even laid off when projects are idled. For employees engaging in these advance and complex tasks, those that are absent from their job for a long time and then return rarely return to optimal form – they can forget how to perform some tasks and how to work together during their time away, and consequently their routines that underlie the firm's capabilities become disrupted (Brown, Carpenter & Peterson, 2019; Corts, 2008; Rahmandad & Repenning 2016). Given the threat to their superior capabilities, these firms - having made substantial investment to be further along the learning curve - are naturally inclined to be more protective of their hard-won gains from regressing (Pisano, 1997). On the other hand, firms having inferior capabilities are likely performing less advanced and complex procedures (Stadler et al., 2013), which makes their routines and skills more standardized and codifiable and hence their capabilities less vulnerable to erosion (Le Breton-Miller & Miller, 2015).

Consequently, capability erosion related to the temporary suspension can limit the firm's ability to capture a share of the industry's upside opportunities due to its reduced productivity (Kulatilaka & Perotti, 1998; O'Brien & Folta, 2009). Therefore, firms idling under uncertainty face a tradeoff between reducing current operations costs but facing higher future reactivation costs (i.e., by staying idled now) versus incurring higher current operations costs to save on lowering future reactivation costs (i.e., by reactivating now). For firms having superior capabilities, such reactivation cost in hindering access to such growth by keeping resources idled can be higher due to their greater capability erosion. This effect does not only limit the potential of recovering lost ground, for instance, disruptions in oil production can result in decreased productivity for oil drillers “that persists beyond the rebound in output during the recovery” (Kellogg, 2011: 1962), but also increases the chance of getting locked-out from access to growth opportunities (Ghemawat, 1991). As Dixit (1992) points out that the upside potential of future operations in case of favourable resolution of uncertainty is an important reason why some decision-makers keep operations alive during uncertainty, a similar rationale can drive idled firms to renter the market prematurely before uncertainty resolves so that they can be better positioned when conditions improve.

Taking these arguments together, firms with superior capabilities are more likely to respond to greater uncertainty by reactivating earlier rather than being idled, which risks capability erosion and limits value capture in the future. In other words, firms having superior capabilities incur a higher cost of reactivation by idling longer, as they face a more uphill battle in reversing the ramp-down to restart operations when the industry recovers. Therefore, we predict:

Hypothesis 2: The negative effect of uncertainty on the likelihood of reactivation is weakened for firms with superior operational capabilities.

Hypothesis 3: The negative effect of uncertainty on the likelihood of reactivation is strengthened for firms with strong reactivation experience.

DATA AND METHODS

To empirically test our theoretical framework, we use data from DrillingInfo, RigData, the Texas Railroad Commission (TRC), and the Energy Information Administration (EIA), on all oil and gas drilling permit records of every well drilled in Texas. This industry context and specific activity are appropriate for our analysis on reactivation of idled resources as it allows us to observe discrete choices to reactivate idled resources (Pindyck, 1988) and capture (exogenous) environmental uncertainty – both crucial to test real option theory (e.g., Folta, 2005), while controlling for various sources of firm heterogeneity, alternative idling modes (e.g., Hutt, 1939), market-related risks, as well as alternative decisions that could influence reactivation choices (e.g., scraping/divesting). While natural resources ideal for RO (sources) and wide use to develop RO models (sources), it is traditionally low in growth options, which is a typical focus in strategy. The context also provides the benefit of understanding which resource is idle and which one is active, divested/scrapped, or redeployed – a difficulty in prior studies (Lieberman, Lee, & Folta, 2015: 542). Our sample includes drillers and their rigs that are idled between 2010 and 2022. We focus on drilling rigs that were idled during this period. Our sample contains xx observations. In our sample of xx idled rigs, x% reactivated and x% were divested. These moves occurred after an average of x months - where x percent of those in the sample for at least *one two-year* interval reactivate, but the probably of reactivation declines sharply as the duration of idling increases. At the same time, the probability of being divested increases as idling duration increase. As our econometric model seeks to capture duration effects that could be influenced by alternative decision outcomes related to idled drilling rigs, we make use of a hazard rate model with competing risk.

DV: Our dependent variable is resource reactivation, which takes the value 0 for the idle state, 1 if a rig is reactivated, and 2 for the competing risk (divest/scrap). Specifically, r*esource Reactivation* (status 1) is defined as restarting the rig within our time window of interest.[2] The other alternative outcome is *divestment* (status 2) is defined as the reported selling of the rig with a two-year interval. Divestment registers when the drilling rig is sold in the second-hand market or sold in the scrap market. For rigs sold in the second-hand market, they may be converted to another use by the buyer, or then sold into the scrap market. For rigs sold in the scrap market, equipment and parts are removed and reused for other active rigs needing replacements, or the steal recovered from the abandoned rigs are often sold for scrap to mini-steel mills (Kaiser & Snyder, 2013).[3] These outcomes are relative to the current steady state of remaining idled (status = 0). Rigs can either exit its steady state of remaining idled by being reactivate or be divested after being idled; no rig can both be reactivated and divested in our sample.

IV: Uncertainty: *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. Building on prior work on real options (Folta & O'Brien, 2003; Oriani & Sobrero, 2008), we measured demand *uncertainty* percentage difference of realized demand compared to the predicted level at a given month t (using GARCH models; see also Ross et al., 2022)**.** Accordingly, the conditional variance generated from generalized autoregressive conditional heteroskedasticity (GARCH model) is used to capture uncertainty. This statistical modeling

[2] We use a two-year interval between any two consecutive data reporting dates, which is at two-week intervals given the frequency of reporting in our data.

[3] The financial value of individual sales in the scrap market is low, and companies rarely report income from scrap sales. As a result, the scrap market is the least transparent among the rig markets (Kaiser & Snyder, 2013).

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.

Moderators:

Capabilities: speed in oil and gas drilling is the key capability for drillers to secure future transactions and earn returns (Brett & Millheim, 1986; Kellogg, 2011). The firm's speed in drilling well projects faster than competitors at the same cost (e.g., Hawk et al., 2013; Ross et al., 2022). For instance, drillers who are intrinsically faster at drilling can enhance the performance of their client firms and realize revenue streams for the clients sooner, thereby enhancing the net present value of an oil-gas well. Accordingly, we focus on one particular kind a firm capability – intrinsic speed capabilities – which refers to the ability to execute investment projects faster than competitors at the same cost (Hawk *et al.*, 2013; Pacheco-de-Almeida *et al.*, 2015).

For our measure of the intrinsic firm speed capabilities revealed by the startup, we follow past literature (Hawk *et al.*, 2013; Pacheco-de-Almeida *et al.*, 2015) and use a residual from a first-stage regression to construct a measure of the intrinsic speed capabilities of the firm in order to classify firms as fast firms or slow firms. First, we estimate a first-stage regression using as the dependent variable a firm's drilling rate and a number of independent variables that are systematic determinants of drilling rate for a given well. Specifically, we calculate our measure of drilling rate by taking the total depth of the focal well and then dividing by the total number of drilling days needed to complete the well (using drilling commencement and completion dates). Using this average measure helps smooth out any daily variations during the drilling process (Kellogg, 2011).[4]

For the first-stage specification, we then run the following OLS model using our drilling data at the project well level (indexed for firm i's well w, field f , and time t) regressing a firm's drilling rate for a given well on a set of well-level project characteristics as follows:

$$\begin{aligned} &Drilling\ Rate_{i,w,f,t} \\ &\quad = \beta_0 + \beta_1\, Well\ Type_{w,f,t} + \beta_2\, Project\ Cost_{w,f,t} + \beta_3\, Contract\ Type_{w,f,t} \\ &\quad + \beta_4\, Oil\ Potential_{w,f,t} + \beta_5\, Oil\ Demand_{w,f,t} + \overrightarrow{\beta_6} FIELDDUM + \overrightarrow{\beta_7} PRODUCTDUM \\ &\quad + \overrightarrow{\beta_8} YEARDUM + \theta_{i,w,t} \end{aligned} \tag{1}$$

In this regression, $Drilling\ Rate_{w,f,t}$ is the feet per day drilling rate achieved for the well, $Well\ Type_{w,f,t}$ is the type of well (vertical versus directional), $Project\ Cost_{w,f,t}$ is the cost of the well in thousands of US dollars, $Contract\ Type_{w,f,t}$ is a variable capturing whether the contract is day rate or turn key, $Oil\ Potential_{w,f,t}$ is the expected oil reserves in the current field, $Oil\ Demand_{w,f,t}$ captures demand conditions at the time of the drilling and is based on oil consumption data from the U.S. Energy Information Administration (EIA) in millions of barrels,

[4] We exclude the wells in our data that are missing completion dates because we cannot be certain whether such omissions are due to reporting errors or signify uncompleted wells. We checked with representatives from our data sources (DrillingInfo and the Texas Railroad commission), and both were unable to confirm either using data currently available.

and $FIELDDUM$, $PRODUCTDUM$, and $YEARDUM$ are vectors of dummies capturing fixed effects for each field (based on geography of the drilling), product type (oil versus oil and gas) and year.

The intuition behind this regression is that we are decomposing the realized drilling rate of the well into a set of systematic determinants captured by the explanatory variables. We then decompose the realized drilling rate into the remaining firm-specific idiosyncratic component of drilling speed as embodied in the residual, $\theta_{i,\mathrm{w},t}$. This residual represents firm-specific deviations from systematic expected drilling rate for a given well. For instance, a driller may be able to drill faster by taking on technically less-complex projects. In our context, oil wells that only require 'vertical' drilling are the least complex for the driller to execute, while those that require 'multi-directional' drilling are the most technically complex. Our setup accounts for such systematic differences at the project level as well as in the environment. If the residual is positive, it captures the degree to which the firm realizes a faster than systematic expected drilling rate for the given well. If the residual is negative, it captures the degree to which the firm realizes slower than systematic expected drilling rate for the given well. This residual, then, becomes the basis for our measurement of the driller's capabilities: $Capabilities = \theta_{i,\mathrm{w},t}$. While we do not have access to survey measures, we are able to directly overver a driller's past performance and safety record based on the numbers. Tracking past accidents is also consistent with Folta (2005) that argue that accidents can influence entry thresholds and option exercise decisions (Folta, 2005).

Controls:

Rig technology: We construct a driller's *technology* as the average of its rig horsepower across its rig fleet.

Rig profitability: *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.

Rig experience: 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 experience* is measured as the number of previous wells drilled and completed in the rig's current field.

Rig Automation: we determined whether the focal rig being considered for idling is a traditional rig (=1) or an automated rig that deploys only few or no crew members onsite to operate (=0). Rigs that are flagged in the data as 'automated' could be 'semi-automated' such that a skeletal crew still remains onsite during the drilling process (usually 2, rather than the usual 6-8 members on traditional rigs), or they could be 'fully-automated' rigs requiring no crew members to be onsite. We sought initially to construct an ordinal measure for the degree of automation; however, we were not able to observe the different types of automation and thus deployed a dummy variable as a proxy of our construct of automated or not (=0/1).

Reactivation experience: is measured as the number of previous instances that the driller has idled then reactivated its rigs in the past. Prior experience performing a given task allows better performance of that task due to developing more expertise about the underlying task as well as developing better routines and learning how to coordinate with team members on executing those activities (Argote et al., 1990; Epple et al., 1991).

Idling duration: is measured as the number of months that the focal rig has been idled. The longer the idling, then the longer possible capability erosion (Ross et al., 2023).

Size: which is measured as the number of rigs owned and operated in the driller's fleet, because larger organizations can shift and reallocate resources within to better adjust to uncertainty (Lee & Makhija, 2009).

Public: Drillers that are private are likely to face greater financing constraints than their public counterparts. A main reason is that private firms often incur a higher cost of external capital compared to public firms due to for instance greater information asymmetry between outsiders and insiders (Saunders & Steffen, 2011; Gilje & Taillard, 2016).

Competitive density: 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.

Competitors Idling-Reactivation: 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.

Market growth: control for ***environmental munificence***, which indicates the degree of growth or decline within an industry over the measured period, because such external conditions can determine incentives for firm idling and other exiting decisions (Anderson & Tushman, 2001). Following McNamara et al. (2008), we first regressed industry sales on a year-counter variable (using a five-year window, with last year being the event of interest). Then, we took the estimated regression coefficient, then divided by the mean value of industry sales over the measured period (to indicate the degree of growth or decline within an industry over the measured period).

Empirical Approach

We take a hazard approach to estimate the likelihood that a drilling rig gets reactivated using a competing risks regression that considers alternative events (i.e., divest by scrapping/selling the rig) that can cause a drilling rig to leave its current position (Upson, Ketchen, Connelly, & Ranft, 2012). This is similar to continuous-time event history analysis with partial likelihood estimation and time-varying covariates (Allison, 1984; Greene, 2003; Yamaguchi, 1991). The limitation with event history analysis is that – while the model analyzes the likelihood that the firm in a steady state (in our case, remaining idled) will leave that state for event 1 (in our case, reactive) – is assuming only one way to leave that steady state and thus cannot accommodate other events to leave that steady state (i.e., divested). Event history analysis would simply compare this alternative event of reactivated with the residual condition of not reactivating, but this is problematic because doing this would censor the other competing event of divestment by lumping together two very different outcomes of remaining idled and being divested.

The competing risks model accommodates multiple outcomes to leave that steady state (in case, reactivating or divesting). In particular, competing risk hazard model uses an event-specific cumulative incidence function (Fine & Gray, 1999), which represents the probability that a firm in a steady state (i.e., remaining idled) will experience a certain event that cause it to leave that state (i.e., being reactivated) before a given time *t*, while accounting for a competing event that could also cause the firm to leave its steady state (i.e., being divested). Thus, the likelihood of reactivating is not only a function of the hazard for reactivating but also is a function of the hazard of divestment, because the latter event impedes the former event from occurring.

To derive the cumulative incident of the event of interest by taking account of the competing risk, we first calculate the Kaplan-Meier estimation of the overall survival from any event (i.e., either reactivation or divestment). For a given interval of consecutive periods t_{j-1} and t_j , the overall survival probability up to event time t_j :

$$S(t_j) * \prod_{i=1 to j} (n_i - \frac{d_i}{n_i})$$

Where n_i be the number of event-free rigs up to time t_j .

Sample selection bias concern:

Our sample includes only drillers that have idled out, yet there remain drillers that kept its rigs idled through our sample period (about 19% of all drillers in our sample). Therefore, there is potential for sample selection bias, such that drillers that choose to idle their rigs may be inherently different than those that did not, and such differences may not be captures by our host of controls. Drawing on prior studies that have sought to address this endogeneity concerns using hazard models (i.e., Hoang & Rothaermel, 2010; Jiang, Cannella, Xia, & Semadeni, 2017), we run a two-stage instrumental variable model where we first predict that likelihood that the driller chooses idling using a probit model, and then we run our main regression model that includes as a control the derived residual correcting for possible sample selection bias. While traditionally the two-stage Heckman model is used to derive the inverse mills ratio, the non-linearity of our outcome variable requires this approach to be adjusted.

Specifically, we use a two-stage residual inclusion (2SRI) estimation model, which is a particularly suitable approach for addressing endogeneity bias in non-linear models involving dichotomous and trichotomous 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 instrument we use in the first stage is whether the focal rig has been recently upgraded in the past year, which likely reduces the attractiveness of idling because an incentive for the driller to idle a rig is to upgrade it with new technology, but does not directly affect reactivation. This instrument *rig upgraded* significantly decreases 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 reactivated is also checked, and they are unrelated (r=0.03, n.s.). 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).

RESULTS

We begin with descriptive statistics and a correlation table presented in Table 1. Looking at the correlation matrix in Table 1, we see initial evidence of the negative effect of uncertainty on reactivation. More importantly, we can also see some initial evidence about the firm's resources and characteristics that are positively associated with its reactivation: that the firm's capabilities, relational ties, and safety reputation are all positively correlated reactivation. These simple correlations give some initial results regarding our research questions, but it does not account for the full model specification, omitted variable bias, or the assortment of econometric challenges highlighted above in the section on identification strategy. As a cautionary step, we checked variance inflation factors (VIFs) to see if multicollinearity is at problematic levels. All VIFs were below 10 with the mean VIF of 1.751 and a max of 3.27, suggesting multicollinearity is at acceptable levels.

[Insert Table 1 about here]

In Table 2, we model the cumulative incident of reactivation to determine what is the probability of reactivation within our time window of interest. We use standard coefficients (not hazard rates) to make interpretation easier – a positive (negative) coefficient sign indicates a greater (lower) hazard of the focal event occurring (i.e., reactivation), and thus can be interpreted to mean that the predictor of interest leads to faster (slower) occurrence of the focal event. Model 1 includes only the controls. In Model 2, we find that uncertainty has a negative and significant effect on the likelihood of reactivation (p=.002).

In Model 3, we test our first moderator, a firm's capabilities. We find that the coefficient of uncertainty remains negative and significant (p=.004); the coefficient of the firm's capabilities is positive and significant (p=.028); and the coefficient of the interaction term of uncertainty and capabilities is positive and significant (p=.010). These results suggest that the firm having superior capabilities alleviates the negative relationship between uncertainty and the likelihood of reactivation.

In Model 4, we test our second moderator, a firm's reactivation experience. We find that the coefficient of uncertainty remains negative and significant (p=.036); the coefficient of the firm's reactivation experience is positive and significant (p=.078); and the coefficient of the interaction term of uncertainty and reactivation experience is negative and significant (p=.023). These results suggest that the firm having stronger reactivation experiences ehances the negative relationship between uncertainty and the likelihood of reactivation.

To further the interpretation of our results, we also plotted the cumulative incidence curves to visually represent the competing risks. These plots are based on the parameter estimated using subhazard ratios, which measures the effects of our main variable of uncertainty on the cumulative incidence of reactivation with the competing risk being divestment. In particular we plot the cumulative incidence curves for high and low uncertainty levels (based on one standard deviation above and below the mean value of uncertainty, respectively). Because we are considering the moderation effects, we decided to simplify the interpretation the cumulative incidence curves by plotting the above relationship between our direct effect of uncertainty on the cumulative incidence of reactivation using subsamples of high and low values of our moderator. As our plots show, the subhazard ratio for high uncertainty is less than the subhazard for the control for low uncertainty group. In other words, those subject to the treatment group have a reduced incidence of reactivation, which such reduction can be visualized.

Specifically, for the moderator effect of capabilities, we plot the cumulative incidence curves of uncertainty for firms having high capabilities (based on one standard deviation above the mean) and for firms having low capabilities (based on one standard deviation below the mean). As Figure 1a shows for firms having high capabilities at the mean values for controls, the probability of reactivation within 20 months is roughly 20% under low uncertainty and drops to 10% when uncertainty increases to high. Then as Figure 1b shows for firms having low capabilities at mean values for controls, the probability of reactivation within 20 months is roughly 18% under low uncertainty and drops to 8% when uncertainty increases to high. In other words, when comparing these figures, we see that under high uncertainty firms having high-level capabilities are more likely to reactivate than firms having low-level capabilities.

DISCUSSION

We find that demand uncertainty is negatively related to the likelihood of reactivating idled resources. This effect is reduced for firms with superior capabilities, strong relational knowledge, and strong industry reputation (see preliminary results table below). Our paper seeks to contribute in various ways. First, we contribute to the real options literature empirically by providing evidence of the uncertainty-reactivation relationship. Whereas prior work on real options pointed out that uncertainty motivates firms to keep the option to invest open (e.g., Dixit & Pindyck, 1994) and had shown that external forces could encourage firms to invest in the presence of uncertainty (e.g., Folta & O'Brien, 2004), we contribute theoretically by revealing internal factors linked to erosion concerns that determine the exercise of real options. These insights help better understand hysteresis in cyclical markets and demand shocks despite facing the same industry-wide demand uncertainty.

Second, we complement Ghemawat's (1991) theory of commitment, which is "a theory about the trade-off between commitment and flexibility in uncertain situations" (Cassiman et al. 2022: 132; see also Leiblein, Reuer, Zenger 2018), by providing empirical insights on firm-specific motives to invest linked to attempts to avoid commitment due to "lock-out" rather than the commitment effects of "lock-in" typically studied in strategy. We thus contribute to research on strategic decisions by providing insights into the conditions under which decision-makers consider the "intertemporal consequences of today's decisions on the value of tomorrow's choices" (Leiblein et al., 2018: 566). These insights shed light on canonical issues in strategy, such as how do firms behave and why are firms different (Rumelt et al., 1994).

Finally, we contribute to the resource-based perspective by introducing the notion of resource reactivation as a subprocess in resource management (Sirmon et al., 2007) and how reactivation is used as a curatorship function and to mitigate resource vulnerabilities under uncertainty (Le-Breton Miller & Miller, 2016). Building on what Hutt (1939) had coined in economics the "*Theory of idle resources*" and integrating it with modern resource-based perspective in strategy and an evaluation tool to capture the role of uncertainty (i.e., real option theory), we shed light on conditions under which resource reactivation creates value.

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Table 1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Reactivation	1																			
2. Uncertainty	-0.19	1																		
3. Capabilities	0.15	-0.07	1																	
4. Reactivation Exp	0.12	-0.03	0.05	1																
5. Rig Tech	0.09	-0.04	0.01	0.01	1															
6. Rig Profit	-0.05	0.02	0.03	0.17	0.01	1														
7. Rig Experience	0.04	-0.04	-0.01	-0.01	0.02	0.02	1													
8. Rig Automation	0.07	-0.03	-0.00	0.02	0.01	0.07	-0.01	1												
9. Rig Upgraded	-0.03	-0.02	-0.02	-0.01	0.00	-0.25	0.01	0.13	1											
10. Scrap Value	-0.11	-0.05	-0.03	-0.02	0.02	-0.04	0.02	0.20	0.16	1										
11. Cold Stacked	-0.05	-0.01	0.02	0.01	0.03	-0.02	0.03	-0.01	0.04	-0.23	1									
12. Time Since Last Reactivation	-0.13	0.03	-0.04	-0.09	-0.05	-0.11	-0.02	-0.05	-0.01	0.11	0.14	1								
13. Size	0.03	0.00	-0.01	0.02	0.01	0.03	-0.02	0.03	-0.01	0.04	-0.03	-0.09	1							
14. Lumpiness	0.06	0.28	-0.01	0.04	0.05	0.01	0.09	0.13	-0.03	0.07	-0.04	-0.02	0.00	1						
15. Order Idling Portfolio	0.12	-0.01	0.02	0.01	0.03	-0.02	0.03	-0.01	0.04	-0.14	0.02	0.01	0.01	0.11	1					
16. New Rigs Added Portfolio	-0.15	-0.15	0.13	0.07	0.06	-0.16	0.08	-0.09	0.06	0.02	0.01	-0.01	0.03	-0.02	0.12	1				
17. Competitors Idling-React	0.13	-0.01	0.02	0.01	0.03	-0.02	0.03	-0.01	0.04	-0.00	0.02	-0.04	0.01	0.02	0.01	0.03	1			
18. Market Growth	0.09	-0.03	-0.00	0.02	0.01	0.01	-0.01	0.02	0.01	0.03	-0.02	-0.07	0.04	-0.00	0.02	0.01	0.04	1		
19. Average Driller Payment Fld	0.11	-0.11	0.09	0.13	0.14	0.22	0.18	0.09	0.12	0.05	-0.06	-0.03	0.09	0.01	0.08	0.15	0.13	0.07	1	
20. Nonidled Resources Portfolio	-0.08	0.06	0.10	0.12	0.09	0.07	0.04	0.02	-0.01	-0.11	-0.05	-0.05	0.03	0.02	0.01	0.08	0.11	0.09	0.12	1
VIF (mean VIF = 2.088)	0.86	2.85	1.76	1.89	1.54	3.55	2.32	1.61	1.29	1.82	2.56	2.09	2.49	3.12	2.81	1.82	2.15	3.52	2.51	1.81
mean	0.46	0.21	1.19	13.49	39.50	20.02	27.91	0.21	0.18	13.49	0.13	6.15	18.24	0.15	3.38	1.31	12.52	0.61	1152.15	0.72
S.D.	0.30	0.32	5.465	6.24	16.29	8.19	15.79	0.11	0.11	9.24	0.08	3.95	10.29	0.086	2.52	1.12	9.21	0.39	1218.13	0.48

Table 2

Competing Risk Hazard Model

	Model 1		Model 2		Model 3		Model 4		Model 5	
Rig Tech	-0.002	*(.043)*	-0.002	*(.045)*	-0.002	*(.047)*	-0.002	*(.049)*	-0.002	*(.054)*
	(.001)		(.001)		(.001)		(.001)		(.001)	
Rig Profit	0.004	*(.649)*	0.004	*(.653)*	0.004	*(.656)*	0.004	*(.656)*	0.004	*(.666)*
	(.009)		(.009)		(.009)		(.009)		(.009)	
Rig Experience	0.003	*(.287)*	0.003	*(.292)*	0.003	*(.314)*	0.003	*(.297)*	0.003	*(.314)*
	(.003)		(.003)		(.003)		(.003)		(.003)	
Rig Automation	0.219	*(.142)*	0.215	*(.146)*	0.211	*(.151)*	0.211	*(.150)*	0.198	*(.163)*
	(.149)		(.148)		(.146)		(.146)		(.142)	
Rig Updgraded	-0.050	*(.099)*	-0.047	*(.101)*	-0.046	*(.102)*	-0.044	*(.109)*	-0.045	*(.106)*
	(.030)		(.029)		(.028)		(.028)		(.028)	
Scrap Value	-0.014	*(.033)*	-0.014	*(.035)*	-0.013	*(.037)*	-0.013	*(.037)*	-0.013	*(.043)*
	(.007)		(.006)		(.006)		(.006)		(.006)	
Cold Stacked	-0.305	*(.055)*	-0.299	*(.058)*	-0.293	*(.060)*	-0.293	*(.060)*	-0.276	*(.069)*
	(.159)		(.158)		(.156)		(.156)		(.151)	
Time Since Last Reactivation	-0.612	*(.082)*	-0.59	*(.087)*	-0.58	*(.086)*	-0.585	*(.087)*	-0.551	*(.092)*
	(.352)		(.345)		(.338)		(.341)		(.327)	
Size	0.003	*(.397)*	0.003	*(.402)*	0.003	*(.406)*	0.003	*(.406)*	0.003	*(.421)*
	(.004)		(.004)		(.004)		(.004)		(.003)	
Lumpiness	-0.044	*(.094)*	-0.042	*(.097)*	-0.039	*(.088)*	-0.041	*(.084)*	-0.038	*(.094)*
	(.026)		(.025)		(.023)		(.024)		(.022)	
Order Idling Porfolio	0.036	*(.188)*	0.036	*(.193)*	0.035	*(.197)*	0.035	*(.197)*	0.032	*(.211)*
	(.028)		(.027)		(.027)		(.027)		(.026)	
New Rigs Added Portfolio	-0.276	*(.033)*	-0.268	*(.036)*	-0.243	*(.050)*	-0.233	*(.052)*	-0.206	*(.055)*
	(.130)		(.128)		(.124)		(.120)		(.107)	
Competitors Idling-Reactivate	0.0282	*(.080)*	0.028	*(.083)*	0.027	*(.086)*	0.027	*(.086)*	0.026	*(.096)*
	(.016)		(.016)		(.016)		(.016)		(.015)	
Market Growth	0.003	*(.004)*	0.003	*(.004)*	0.003	*(.004)*	0.003	*(.004)*	0.002	*(.006)*
	(.001)		(.001)		(.001)		(.001)		(.001)	
Average Driller Payment Field	0.008	*(.049)*	0.008	*(.057)*	0.007	*(.054)*	0.007	*(.057)*	0.006	*(.060)*
	(.004)		(.004)		(.004)		(.004)		(.003)	
Nonidled Resources Portfolio	-0.008	*(.034)*	-0.007	*(.037)*	-0.007	*(.036)*	-0.007	*(.037)*	-0.007	*(.044)*
	(.004)		(.004)		(.003)		(.003)		(.003)	
λ (for self-selection)	-0.024	*(.121)*	-0.023	*(.138)*	-0.021	*(.165)*	-0.023	*(.139)*	-0.019	*(.170)*
	(.0157)		(.0156)		(.0153)		(.0156)		(.0137)	
Predictors:										
Uncertainty			-4.581	*(.029)*	-4.443	*(.033)*	-3.5482	*(.036)*	-2.946	*(.034)*
			(2.101)		(2.080)		(1.692)		(1.392)	
Capabilities					0.004	*(.024)*			0.003	*(.029)*
					(.002)				(.001)	
Uncertainty X Operational Capabilities					0.080	*(.014)*			0.073	*(.017)*
					(.033)				(.031)	
Reactivation Experience							1.490	*(.072)*	1.384	*(.078)*
							(.828)		(.786)	
Uncertainty X Reactivation Exp.							-2.402	*(.023)*	-2.185	*(.027)*
							(1.06)		(.985)	
Log-likelihood	-149,352		-148,516		-147,769		-146,119		-143,163	
Pseudo R-squared	0.0115		0.0119		0.0125		0.0236		0.0252	
N	80,672		80,672		80,672		80,672		80,672	

Notes: The unit of analysis is at the rig level. The sample is all rigs that are idled. The dependent variable is whether the rig remains idled (=0), reactivated (=1), or divested (=2). We use a competing risk hazard model. Omitted in this table is the first-stage probit regression that includes our instrumental variable *Rig Upgraded* to estimate the likelihood of that rig being

Idled. The columns shown are the second-stage results that includes a correction for self-selection (λ) into our sample of idled rigs.

Figure 1a & 1b