Do Alliances Make Firms Faster?

Abstract

Alliances are typically viewed as an acceleration strategy for firms able to access or acquire the resources and capabilities of partner firms, yet theoretical and empirical work suggests that alliances can actually impair speed performance due to the costs stemming from partner cooperation and coordination. In this paper, we advance the premise that firm heterogeneity may determine whether alliances enhance, or impair, the speed performance of firms. We then turn to focus on one particular kind of firm heterogeneity, the intrinsic speed capabilities of the firm, by which we mean the ability to execute investment projects or operations faster at the same cost. Our expectation is that slow firms, or those firms lacking intrinsic speed capabilities, will realize substantial speed benefits from partnering due to the capability access from partner firms. We also expect that the benefits enjoyed by slow firms from partnering can persist into future projects due to capability acquisition from the partnership, but that these benefits hinge on the firm possessing absorptive capacity in the form of previous partnering experiences. Results from random coefficient models that address selection concerns and from treatment effect analyses provide support for these expectations in on-shore oil and gas drilling projects.

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INTRODUCTION

In the alliance literature that has developed over several decades, there is a long history of firm speed being invoked as an important reason to do an alliance, given the resources and capabilities firms can access through partnerships. For instance, Ohmae (1989) advised executives, "you should look hard – and early – at forging alliances. In a world of imperfect options, they are often the fastest…way to go global" (p. 147). Similarly, Bleeke and Ernst (1991) emphasized that "alliances are an expedient way to crack new markets, to gain skills, technology, or products, and to share fixed costs and resources" (p. 127). Hamel, Doz, and Prahalad (1989) also stress the speed advantages of alliances, declaring "Time is another critical factor. Alliances can provide shortcuts for Western companies racing to improve their production efficiency and quality control" (p. 133). Current teaching materials in corporate strategy also emphasize firm speed as a reason to do alliances. For instance, in the foundational textbook *Corporate Strategy*, Collis and Montgomery (2005) list speed as a benefit of alliances (p. 97). In the textbook *Strategic Management*, Rothaermel (2019) emphasizes that "Strategic alliances are attractive for a number of reasons. They enable firms to achieve goals faster and at lower costs than going it alone" (p. 313). In sum, practical advice and teaching on alliances has over several decades routinely mentioned the value of alliances in fostering speed.

However, the developing academic research on alliances would also suggest that they are no panacea. There are numerous drawbacks to alliances, some of which might well make them impair, rather than foster, speed performance. Partnerships require a firm to cooperate and coordinate with another organization, which can lead to mistakes and costly delays (Thompson 1967, Gulati and Singh 1998, White and Lui 2005). For instance, a partner might deliberately delay information sharing or slow coordination to exact leverage for better bargaining and terms, which could further cause delays as well (Masten, Meehan, and Snyder 1991, Pirrong 1993, David, Rawley, and Polsky 2013). While systematic empirical research on the speed performance implications of alliances is very sparse, a recent study by Castañer, Mulotte, Garrette, and Dussauge (2014) found that partnering tends to lengthen time to market for new product development projects in aircraft development, reinforcing this potential dark side of alliances in terms of speed performance. Given the likely theoretical tradeoffs involved and the very limited empirical literature on the topic, we are faced with an interesting puzzle: alliances are often portrayed as an acceleration strategy for firms, yet theoretical and empirical work suggests that alliances might actually impair speed performance.

A potential resolution to this puzzle may be that firm heterogeneity may determine whether alliances enhance speed performance or are detrimental to firms. Intuitively, the marginal effect of partnering on speed performance is likely to be firm specific and vary substantially across firms due to the firm-specific nature of resources and capabilities of the firm in executing operations and mitigating coordination costs with partners. In particular, it seems reasonable to expect that slow firms may in particular benefit from partnering in order to accelerate their operations and deliver faster performance to their customers due to their inability to move quickly otherwise. Corroborating this expectation, at a recent conference the VP of external innovation at Johnson and Johnson indicated that firm speed matters in their decision to pursue an alliance to go faster, explaining "We are a slow firm -- we partner to go faster." This reasoning implies that firm heterogeneity in speed may be an important determinant of the alliance speed performance relationship. Firm speed heterogeneity has also been shown to affect the decision of firms to partner or go it alone in the first place (Hawk, Reuer, and Garofolo 2021), but the impact of firm speed heterogeneity on the alliance speed performance relationship has been unexamined, creating a gap in the literature of our understanding of whether alliances can help slow firms go faster, and under what conditions.

The goal of this paper is to examine the speed implications of alliances versus the go it alone alternative. We ask the overall research question: Do alliances versus going it alone result in greater firm speed performance? We begin our investigation by empirically examining the relationship between partnering and speed performance. We then develop theory regarding the role of firm heterogeneity in the speed implications of partnering. Our basic theoretical expectation is that the effect of alliances on firm speed varies substantially across firms, such that firm heterogeneity matters in understanding the effect of alliances on firm speed. We conceptualize the relationship between partnering and speed performance as a firm-specific marginal effect of partnering on speed performance, and we theoretically expect that these firm-specific marginal effects significantly vary across firms due to the firm-specific nature of firm resources and capabilities in executing operations and mitigating coordination costs. We then turn to focus on one particular kind of firm heterogeneity, the intrinsic speed capabilities of the firm, by which we mean the ability to execute investment projects or operations faster at the same cost (Hawk, Pacheco-De-Almeida, and Yeung 2013, Pacheco-de-Almeida, Hawk, and Yeung 2015). Our basic premise is that the speed implications of alliances are contingent on the capabilities of the focal firm to move quickly. Given the substantial potential speed costs of partnering due to partner coordination and conflict, partnering is only likely to increase speed performance when the focal firm is unable to move quickly on its own and stands to benefit greatly from the capabilities of external partners. For these slow firms, partnering is more likely to enhance speed performance rather than being detrimental. Importantly, we also expect the benefits of partnering for slow firms to extend to future projects due to the slow firm developing and improving its own speed capabilities from the partnership via capability acquisition. We further theorize that these benefits in future projects over time hinge on the firm possessing absorptive capacity stemming from previous experiences with alliances. Taken together, our ideas suggest that firm heterogeneity not only helps account for the speed benefits that firms derive, or fail to derive, from an individual alliance project, but also the speed benefits that accrue to them well into the future through the speed capabilities they are able to acquire and internalize. We test these ideas using a variety of identification approaches such as random coefficient models with Heckman corrections for firms' strategic decisions to partner or go it alone and treatment effect analyses (propensity score matching, inverse probability weighting, and doubly robust estimation).

Our study has several implications for scholarship on alliances and competence-based perspectives on interfirm collaboration in particular. First, we replicate the core findings of Hawk et al. (2021) that slow firms are more likely to partner rather than going it alone in a new empirical setting (i.e., oil and gas drilling projects). Replication of core findings from prior studies helps reinforce our knowledge about core ideas in strategy and builds cumulative knowledge (Lee Forthcoming), and our replication results further support the generalizability of the findings of Hawk et al. (2021) in liquified natural gas (LNG) construction projects to another industry setting. We also advance beyond this study to examine the consequences of partnering, by establishing that partnering enhances firm speed performance for slow firms. Due to data constraints, they did not study the performance outcomes realized from partnerships, which in general has been a thorny issue and often difficult to accurately estimate for alliance researchers, as we explain below. We thus help fill this gap and explicitly investigating a key outcome in terms of the speed performance of partnership projects versus go it alone projects using rich data from oil and gas drilling projects. We also explore the temporal dynamics of alliances by investigating the speed performance implications of the focal partnership on subsequent projects, thus speaking to the future implications of capability acquisition from partnerships over time. We show that partnering for slow firms has speed performance benefits not only in a current project but also extends into future projects, and that these benefits are amplified for firms possessing absorptive capacity in the form of partnering capabilities.

Our findings have many implications for both strategy researchers and practitioners. There has been a long history of scholarly and practitioner interest in the performance implications of alliances. Many scholars have emphasized that measuring the performance implications of alliances is very difficult, with each proposed and utilized measure having significant shortcomings. Categories of performance measurements include financial performance, operational performance, and organizational effectiveness, and measurement of these types of performance vary widely and include measurements of survival, satisfaction, termination and shareholder returns, each with its own limitations (Ariño 2003). We contribute to the literature with a comprehensive and rigorous analysis of speed as a unique and interesting performance outcome that has often been mentioned during the past few decades, and we show how this interesting performance outcome from alliances varies across firms due to firm heterogeneity and is a function of the speed capabilities possessed by the focal firm and its ability to develop speed capabilities from the partnership. As we elaborate below, in our empirical setting speed matters a great deal to firm performance and competitive advantage more broadly, so future research can identify other resources and capabilities that potentially contribute to the speed benefits that firms derive, or fail to derive, from alliances. More broadly, our results reinforce and extend ideas from the Resource Based View by demonstrating the importance of firm heterogeneity in the time dynamics of how firms compete and organize firm activities. Furthermore, we build upon and extend both the corporate strategy literature and competitive strategy literature by uniting ideas about intrinsic speed capabilities with firms' expansion mode decisions, highlighting how firm heterogeneity in capabilities and expansion mode selection shape the temporal dynamics of firm performance in current projects as well as in future projects over time.

BACKGROUND LITERATURE ON ALLIANCES AND SPEED

Alliances and Firm Speed Performance

Speed in firm growth or in operations has been emphasized as a potential source of competitive advantage for firms. Indeed, the value of firm speed as a potential source of competitive advantage has been featured in many competitive strategy topics on firm capabilities (Teece, Pisano, and Shuen 1997, Helfat et al. 2007, Teece 2007), first mover advantages (Lieberman and Montgomery 1988, 1998), new product development (Smith and Reinertsen 1998), and time based competition (Stalk 1988, Stalk and Hout 1990). Speed in resource accumulation and in operations can provide many benefits, such as realizing future revenue streams sooner and having earlier access to valuable locations or relationships with suppliers or consumers (Lieberman and Montgomery 1988, 1998). Operational speed can also yield performance benefits by making a firm more responsive to customer needs, more adaptable to change, and quicker to deliver new products to market and to consumers (Stalk 1988, Stalk and Hout 1990). For slower firms, they may also be less adaptable and agile in adjusting their resource deployments and operations, leading to potentially worse service for customers and slower response time in a dynamically changing environment. For these firms, managers may thus wish to assess and consider strategies to overcome their deficiencies in intrinsic speed capabilities and enhance their speed performance.

In this paper, we specifically consider whether alliances represent a means of project acceleration for firms. To do so, an important aim of our study is to connect research on alliances and other means of organizing projects such as autonomous development that have been featured in the corporate strategy literature (e.g., Capron and Mitchell 2012) with the foregoing research on speed in the competitive strategy literature. This requires us to first consider the theoretical drivers underlying alliances that may enhance speed performance or be detrimental to it.

Alliances have several theoretical properties that may yield speed benefits to a firm versus the alternative of autonomous development. First and foremost, alliances may be a way for firms to access needed resources and capabilities needed for operations or the development of investment projects, and the external sourcing of these resources and capabilities may be done faster than developed organically via the autonomous alternative. Capability access has been emphasized as a major resource- and capability-based motivation for alliances (Barney 1999, Ahuja 2000, Hitt, Dacin, Levitas, Arregle, and Borza 2000, Hitt, Ahlstrom, Dacin, Levitas, and Svobodina 2004), and this capability-seeking motivation is likely to stem at least in part from temporal considerations. Rather than facing lengthy resource accumulation lags needed to develop a particular capability or accumulate a needed resource, a firm may be able to bring on a corporate partner that already possesses the capability set or resource endowment that the focal firm is lacking. For instance, by partnering and thereby tapping into knowledge and other resources and capabilities with quasi-public goods characteristics, the focal firm may be able to sidestep the time compression diseconomies and resource accumulation lags typically associated with internal development of the capabilities or resources that are presently deficient at the focal firm, and thus enhance speed performance. Note that partnerships provide two potential mechanisms for the focal firm to overcome a capability or resource deficiency: capability access, where the focal firm can benefit from the capabilities and resources of the partner firm deployed to the focal operation or development project; and capability acquisition, where the focal firm can learn and absorb the capabilities possessed by the partner firm for current as well as future use (Grant and Baden-Fuller 2004). Whether capabilities and resources are merely accessed or potentially acquired via partnership, sourcing useful capabilities from a corporate partner via alliances may enable firms to enhance their speed performance.

Alliances, however, also have several theoretical properties that may be detrimental to firm speed performance. It is well known that they are subject to potential coordination problems and conflicts between partners that would be mitigated in autonomous projects within a single organization (Thompson 1967, Gulati and Singh 1998, White and Lui 2005). Such difficulties may aggravate time compression diseconomies and resource accumulation lags due to mistakes, delays and rework, thus resulting in speed impairment rather than enhancement. In partnerships, the focal firm and the partner firm must share information and coordinate activities due to interdependent activities associated with the collaborative operations and resource development that embody the partnership. An extensive literature has documented how the sharing of information and coordination of activities across organizational boundaries may result in less efficiency than keeping activities within one corporate entity and going it alone (Allen, Lee, and Tushman 1980, Kogut 1989, Williamson 1991, Griffin and Hauser 1992, Langlois 1992, Monteverde 1995, Teece 1996, Hatch and Mowery 1998, Chesbrough and Teece 1999, Leiblein, Reuer, and Dalsace 2002, Qian, Agarwal, and Hoetker 2012, Castañer et al. 2014). Partnerships may therefore result in numerous coordination inefficiencies, which can lead to delays or errors, particularly when tight coordination is required between partners. Partner firms may lack a common language (Foss 1996), and it can be cumbersome and inefficient to share tacit knowledge through unstructured dialogue during cooperation (Monteverde 1995), which may cause delays and rework and impair speed performance. Inter-partner conflicts can emerge and also exacerbate delays, whether unintentionally from errors or intentionally for bargaining reasons (Masten et al. 1991, Pirrong 1993, David et al. 2013). For all of these reasons, alliances may in fact result in worse speed performance relative to the autonomous alternative.

In sum, the speed implications of an alliance versus the autonomous alternative can be characterized as the sum of speed-enhancing resource and capability-based considerations and the speed-impairing considerations associated with partnership coordination challenges and conflicts. Inasmuch as each set of theoretical forces impact resource accumulation lags and time compression diseconomies, they have a bearing on the net effect of alliances on firm speed performance, as we discuss below.

RESEARCH HYPOTHESES

Firm Heterogeneity, Alliances and Speed Performance

Our basic theoretical premise in this paper is that the net effect of partnering on firm speed is likely to be dependent on a variety of firm-specific considerations that affect the tradeoff between the speed-enhancing resource and capability-based considerations and the speed-impairing coordination and conflict considerations. We have submitted that firms are likely to differ in the resource and capability-based considerations that might yield speed benefits from a partnership. For instance, some firms might be more deficient in needed capabilities and resource than others, raising the potential speed benefits of partnerships versus the autonomous alternative. Other firms, however, may have sufficient endowments of needed capabilities and resources, resulting in little or no potential speed benefits of partnerships. Similarly, firms are likely to differ in the coordination challenges and conflicts they experience in alliances. Some firms may be particularly adept at navigating coordination issues and information sharing as well as minimizing partner conflict (e.g., Hoang and Rothaermel 2005, Argyres and Mayer 2007, Heimeriks, Bingham, and Laamanen 2015). These firms may minimize the speed costs from coordination and conflict considerations. Other firms, however, may lack experience and skills at managing inter-firm coordination and conflict, causing the speed costs of an alliance to escalate. Each firm therefore will have a firm-specific net speed effect of partnerships versus the autonomous alternative, and this firm-specific effect will likely vary a lot across firms. In short, we expect that firm heterogeneity matters for the speed implication of alliances. That is, the speed performance implications of alliances versus the autonomous alternative generally varies across firms rather than being uniform across firms. Some firms may have positive marginal effects of partnering on speed performance, whereas other firms may have negative marginal effects of partnering on speed performance due to the firm-specific tradeoff considerations articulated above. We thus obtain the following hypothesis as a baseline prediction to be unpacked in subsequent predictions:

Hypothesis 1: The marginal effect of partnering on speed performance varies significantly across firms.

Speed Performance Implications of Partnering for Slow Firms

While the foregoing discussion emphasizes firm heterogeneity in the relationship between partnering and speed performance, we would also like to begin to identify specific forms of heterogeneity that can explain the degree to which firms benefit from partnering or not. While we expect that many different resources and capabilities are sources of firm heterogeneity that can alter the speed implications of alliances, given the distinctive focus on speed in this study, we focus on firms' intrinsic firm speed capabilities, by which we mean the ability of firms to execute investment projects or operations faster than competitors at the same cost (Hawk et al. 2013, Pacheco-de-Almeida et al. 2015). Our basic premise is that the intrinsic firm speed capability of the focal firm is likely to affect the theoretical tradeoffs that determine the speed performance implications of a firm choosing an alliance versus the autonomous alternative. Intrinsic speed capabilities represent a firm skillset that captures firms' abilities to execute investment projects faster than competitors at the same cost. For intrinsically fast firms, the barrier of time compression diseconomies accompanying autonomous development is less severe than for slower competitors, enabling intrinsically faster firms to complete operations or investment projects with shorter time lags than slower comparable firms. This skillset, thus, should be of prime consideration when the firm assesses the resource and capability-based speed benefits of alliances given the potential speed costs of alliances.

First, consider a firm possessing above average intrinsic speed capabilities. This firm already has an endowment of firm skills that enables the firm to execute operations or investment projects by itself at an above average pace. This firm, thus, has a pre-existing competitive advantage in terms of speed performance. The potential benefits to source and access the capabilities and resources of other firms via alliances are therefore likely to be lower than for firms without intrinsic speed capabilities or even non-existent. We therefore anticipate that they are unlikely to offset potential costs due to partner coordination and conflict. The fast firm must deal with another corporate entity in the partnership and faces frictions associated with difficulties and errors in coordination across partners and potential conflicts in the partnership which further may cause delays. Given the minimal resource and capability-based speed performance benefits and potentially substantial speed costs related to coordination and conflict, we expect that partnering is likely to result in lower speed performance for intrinsically fast firms.

Conversely, consider a focal firm with below average intrinsic speed capabilities, i.e. an intrinsically slow firm. This firm has a deficiency in internally-based speed capabilities and is, thus, unable to execute operations or investment projects faster than competitors on its own. For this slow firm, the resource and capability-based speed benefits of alliances are likely to be substantial: a partner firm may be able to provide needed capabilities and resources to the focal firm via the partnership, enabling the focal firm to reduce time compression diseconomies and resource accumulation lags. Of course, the partner firm must derive financial or other benefits of the alliance in return, and these might include market access and growth, capacity utilization, access to other capabilities, risk sharing, or other benefits. For instance, Ireland, Hitt, and Vaidyanath (2002) highlight more than a dozen theoretical perspectives providing accounts for partner motives. Additionally, a seminal paper by Kogut (1988) summarized the motivations in three broad theoretical categories (transaction costs, strategic behavior, and organizational knowledge and learning), and since that time the literature has incorporated insights from economics and sociology that suggest factors that might be beneficial for firms. In addition, for the focal firm speed costs of alliances due to potential coordination challenges and conflicts exist, but it is more likely that the net speed effect is positive in this case relative to the case when a comparable focal firm is fast. This reasoning suggests that, first, slow firms are more likely to partner than going it alone, as predicted and shown in Hawk et al. (2021). Second, it also follows from this reasoning that intrinsically slow firms that partner have a higher likelihood of obtaining faster speed performance than going it alone relative to other firms. Thus, we posit:

Hypothesis 2: The speed performance benefits of partnering versus going it alone will be greater for slow firms.

Temporal Dynamics of Partnering and Speed Performance for Slow Firms

The next pasture of our theoretical development focuses on temporal dynamics of our theory beyond the focal project into future projects. Our expectation is that the speed benefits of partnering for slow firms may extend to future projects since the benefits of partnering may entail both capability access as well as capability acquisition. The literature on alliances emphasizes that there are two main theoretical mechanisms underlying how firms source capabilities via partnerships: capability access and capability acquisition (Grant and Baden-Fuller 2004). In the former case, a firm may tap into the capabilities of the partner firm in an alliance, where the endowment of capabilities of the partner firm are utilized in the focal project. In the latter case, the focal firm might acquire, or internalize, the capabilities of the partner firm in an alliance via learning, thereby enhancing the development of capabilities of the focal firm to be used in future projects. The theoretical mechanism of capability acquisition therefore raises the possibility that the capability benefits of a partnership for a focal firm may extend over time into future projects.

We thus extend our theoretical development to incorporate the possibility that the speed performance benefits of a partnership for a slow firm may extend beyond the focal project into future projects. Intrinsically slow firms may engage in both capability access and capability acquisition in a partnership. A slow firm is likely to engage in accessing the capabilities of a partner firm to be deployed to the focal project to enhance performance. In this process, the slow firm may also engage in capability acquisition by absorbing information from the partner firm, gleaning insights about the processes and operations of the partner firm, and beginning to develop and enhance its own capabilities to execute operations faster (e.g., Lyles and Salk 1996, Dhanaraj, Lyles, Steensma, and Tihanyi 2004). The partner firm may also teach the slow focal firm during the collaboration process, further enhancing capability development in the focal firm. These benefits from the focal project thus may extend to the next few projects, but this benefit may also diminish over time due to organizational forgetting from changes in internal teams of engineers or other human capital and industry dynamics over time as the firm takes on new projects (Ingram and Baum 1997). These possibilities for capability acquisition thus yield our theoretical prediction that the benefits of partnerships for slow firms may extend into future projects yet diminish over time. We thus obtain the following prediction:

Hypothesis 3: The speed performance benefits of partnering versus going it alone enjoyed by slow firms will persist yet diminish into future projects.

The Ability to Acquire Capabilities from Partnerships for Future Projects

While the prior prediction suggests that the benefits of partnerships for slow firms may extend into future projects, we also expect that there is heterogeneity in the extent to which firms can derive such benefits into the future. In particular, in order for a slow firm to benefit in future projects, it must be able to use capability acquisition in the partnership rather than relying only on capability access. In other words, the focal firm may merely access the capabilities of the partner firm for the focal project and thereby avoid the development of its own capabilities, or engage in the process of capability acquisition, where the focal firm acts as a sponge and absorbs insights and teachings to help internally develop its own capability set (Lane, Salk, and Lyles 2001). To realize benefits beyond the focal project, the focal firm must successfully engage in the learning process and acquire capabilities during the initial focal project. Otherwise, any potential benefits beyond the focal project are likely to be minimal or non-existent.

We expect that firms are likely to differ in their ability to achieve capability acquisition in the focal project and thereby realize benefits into future projects. In particular, we focus on one particular type of firm heterogeneity, absorptive capacity through collaborative experience. Firms are likely to differ in their ability to receive and process information in an alliance and learn from a partner firm. Absorptive capacity has been emphasized in the strategy literature as an important ability of firms to digest and process information revealed from the competitive environment (Cohen and Levinthal 1990, Zahra and George 2002, Zou, Ertug, and George 2018). Additionally, there is a long tradition in the alliance literature emphasizing how firms may differ in their ability to process and digest information in the context of an alliance during the collaboration process. Collaborative experience, or the accumulated experience of managing alliances, has been shown to develop collaborative capabilities in firms that enable them to more effectively process and digest information during the collaboration process (Kale, Dyer, and Singh 2002, Heimeriks and Duysters 2007). Our theoretical expectation is that firms with accumulated collaborative experience can enhance the ability of firms to absorb information in the focal collaboration, enhancing the ability of the focal firm to successfully develop capabilities internally and achieve capability acquisition. This expectation suggests that collaborative experience is likely to enhance the benefits of partnering for a slow firm and extend these benefits into future projects over time. We thus obtain the following prediction:

Hypothesis 4: Greater collaborative experience amplifies the positive effect of slow firms partnering rather than going it alone on their speed performance in future projects.

METHODS

Context: Oil and Gas Drilling Projects

Our empirical setting is on-shore oil and gas drilling in Texas. In this setting, a firm known as a 'driller' is contracted by the owner of the well site known as the 'producer'. This driller undertakes the task of penetrating through strata of rocks creating drillhole borings known as wells to eventually reach oil-gas reserves buried deep underground. Such drilling on a well site is done by machinery known as a rig, which is a tall derrick run by a motor that spins a pipe attached to a drill bit to crush through the layers of rocks. For a given well site, a driller can take on the project alone (autonomous operation) or it can elect to partner with another driller to help with the drilling (partnership project). After drilling is completed, the producer then works with other contractors to extract the accessed oil-gas for eventual processing and sale.

The drilling process is standardized in many ways for conventional wells: drilling rigs under contract operate continuously (i.e., 24 hours a day, seven days a week), rotating crews working on the rigs in three 8-hour shifts. Yet drillers differ in their capabilities, which contribute to their performance variation. One reason is that drillers vary in their technologies, such as some having more horsepower in their rigs than others. Another reason is that drillers vary in their operational efficiency. For instance, some drilling crews are able to perform certain routines in parallel like checking for overheating while minimizing operational disruptions, while other crews less adept (Crichton 2005). Drillers can also differ in their expertise on a given well site. A driller having more related task experience, such as by having previously worked on nearby well sites composed of similar geology, can achieve higher operational efficiency (Stringfellow, Domen, Camarillo, Sandelin, and Borglin 2014).

In this setting, speed is a critical determinant of a driller's performance. Faster drilling, or the speed with which the driller can reach the oil and gas reserves underground, will be highly valued by clients because completing a well sooner can result in greater cost savings and an earlier start to oil-gas production to generate revenue (Kellogg 2011). Faster drilling also accelerates information revelation about each well's oil potential, which enables the driller to make faster decisions about committing further or redeploying firm assets to other promising areas. Finally, faster drilling also yields reputational benefits for the driller in the industry, which can help attract future business opportunities. For these reasons, the onshore drilling industry represents a setting where firm speed is strategically important for firm performance.

For each drilling contract for a well site, the focal driller chooses whether to work on the project alone or to partner with another driller as a subcontractor to help. The focal driller choosing to partner can seek access to outside expertise and technologies to potentially boost drilling speed. However, partnering can also require costly coordination and adopting additional routines (and replacing existing ones), which can potentially be very operationally disruptive. Thus, a focal driller being contracted must consider whether the benefits of partnering outweigh the costs.

Data and Sample

The main sources of our data are DrillingInfo, RigData, and well permit records obtained from the Texas Railroad Commission (TRC), which is the regulatory commission responsible for all oil-gas drilling in the state. We also relied on data from the Energy Information Administration to capture macro-economic conditions in the oil-gas industry, such as oil prices, and demand and supply levels in the U.S. Our sample period is from 1995 to 2015.

By combining the datasets, we are able to compile the following information for each observation: the well site identification, the identity of the driller, any subcontracted driller (if drilling is done in a partnership), and the producer holding the land lease on the well site. In our constructed dataset, we are also able to observe in rich detail the features of the well site being drilled, such as its location (e.g., identifying its oil field and county), its depth, and its drilling complexity (whether standard vertical or more complex directional drilling is required). For each well site, we can identify the lead driller, which serves as the focal firm for our analysis. In addition, we can identify whether or not there was another partner driller subcontracted on that well site. After merging this information with needed covariates described below, our final sample consists of 11,572 drilling contracts, comprised of 7,985 contracts where the driller goes it alone, and 3,587 contracts where the driller partners with another drilling firm.

Baseline Statistical Method

The relationship between partnering versus going it alone and speed performance can be expressed in the following baseline linear model:

$$SpeedPerformance = \beta^0 + \beta^1 Partnering + \boldsymbol{\beta^2 X} + \varepsilon \tag{1}$$

where $SpeedPerformance$ is a measure of the speed performance realized in a given project, $Partnering$ is a dummy equaling 1 if the project was done in partnership with another firm and 0 if the focal firm goes it alone, and $\boldsymbol{X}$ is a vector of control variables accounting for other determinants of speed performance of the project.

The core theoretical premise of our paper is that firm heterogeneity should affect the partnering – speed performance relationship. To study the role of firm heterogeneity, we thus augment the baseline model above by specifying a linear random coefficient model as follows:

$$SpeedPerformance = \beta_i^0 + \beta_i^1 Partnering + \boldsymbol{\beta^2 X} + \lambda + \varepsilon \tag{2}$$

where λ is the inverse mills ratio obtained from a first-stage selection model of whether the firm chooses to partner or go it alone in order to account for unobservable factors driving firms' strategic choices to go it alone versus partner and thereby control for governance endogeneity (Shaver 1998, Hamilton and Nickerson 2003, Castañer et al. 2014). Importantly, the coefficient β_i^1 on the variable $Partnering$ is indexed for firm i and estimated using a random coefficient model, where $\beta_i^1 = \beta^1 + u_i^1$, where u_i^1 is randomly distributed following a normal distribution with mean 0 and standard deviation σ, i.e.,

$u_i^1 \sim N(0, \sigma)$. In this approach, β^1 is the overall mean effect of partnering on speed performance and u_i^1 represents firm specific offsets of the coefficient from the average effect β^1, meaning that the marginal effect of partnering on speed performance is allowed to vary across firms, ie, $\beta_i^1 \sim N(\beta^1, \sigma)$. Additionally, we also allow the intercept β_i^0 to be a random coefficient which acts as a random firm effect to account for potential time invariant omitted firm heterogeneity.

Random coefficient models allow the analyst to obtain a distributional estimate of a marginal effect of interest, yielding an estimate of the first and second moments of the distribution. These estimates enable the analyst to study the nature of firm heterogeneity in the relationship of interest by looking at the significance of the mean and standard deviation estimates of the random coefficients (Alcácer, Chung, Hawk, and Pacheco-de-Almeida 2018). The significance of the mean of the random coefficient is analogous to a traditional average marginal effect in a typical regression, capturing an average effect across firms. The significance of the second moment, however, can give additional insight into the nature and importance of firm heterogeneity in the relationship of interest, and this parameter becomes the central focus for our purposes to test our theory. If the variance estimate of the random coefficient is insignificant, the marginal effect applies uniformly across firms. In other words, the slope estimate from the RCM model holds for all firms in the sample, and firm heterogeneity does not significantly matter in the focal relationship of interest. If the variance estimate is significant, however, this suggests that firm heterogeneity is important in the relationship of interest (i.e., marginal effects significantly vary across firms). Using this methodology, the use of a random coefficient model enables us to test the first part of our theory as follows. In hypothesis 1, we predict that the firm-specific marginal effect of partnering on speed performance varies significantly across firms. We can test this prediction using the second moment estimate of the random coefficient estimate in equation (2). Our prediction in hypothesis 1 corresponds to the expectation that $\sigma > 0$. The distributional estimate can also inform our understanding of whether some firms can enhance speed performance a great deal and/or if other firms destroy speed performance by partnering. Specifically, an attractive feature of random coefficient models is we can also obtain firm-specific predictions of the marginal effects via BLUPs (best linear unbiased predictions), enabling us to graphically depict firm-specific marginal effects and observe which firms create or destroy speed performance by partnering, thereby vividly displaying the nature of firm heterogeneity in the theoretical relationship of interest and yielding firm-specific insights from our large sample econometrics (Alcácer et al. 2018).

We then hypothesized about a particular type of firm heterogeneity that may matter in shaping the speed performance implications of partnering versus going it alone. In particular, we focus on the intrinsic speed capabilities of the firm, with the intuition that partnering is likely to affect speed performance differently for fast firms versus slow firms. Specifically, hypothesis 2 predicts that partnering will enhance the speed performance of slow firms. To test these predictions, we take the marginal effect β_i^1 in equation (1) and make it a function of a firm's deficiency in intrinsic speed capabilities to express this idea as follows:

$$\beta_i^1 = \alpha_i^0 + \alpha^1 Slowness \tag{3}$$

where $Slowness$ is our measure of the intrinsic slowness of the firm. Substituting this expression back into equation (2), we obtain the following expression:

$$SpeedPerformance = \beta_i^0 + \alpha_i^0 Partnering + \alpha^1 Slowness * Partnering + \boldsymbol{\beta^2 X} + \lambda + \varepsilon \tag{4}$$

In hypothesis 2, we expect partnering to be speed performance enhancing for slow firms. This prediction corresponds to the theoretical expectation that $\alpha^1 > 0$.

Next, we focus on the persistence of this effect beyond the focal project into future projects. Our expectation in hypothesis 3 is that the benefits of partnering for slow firms may extend into future projects but diminish over time. Moreover, we expect in hypothesis 4 that these benefits in future deals hinge upon and are amplified by the collaboration capabilities of the focal firm. To investigate these theoretical expectations, we constrain the sample to future deals for intrinsically slow firms beyond the focal alliance. We then adjust our model to focus on a series of dummies that index the order of future projects of the firm beyond the focal alliance (i.e., dummies indicating the second deal, third deal, etc.), and a series of interaction terms between these future deal dummies and collaboration experience as follows:

$$SpeedPerformance = \beta^0 + \sum_{j=2}^{J} \alpha_j * DealDummy_j + \sum_{j=2}^{J} \alpha_j^{PartneringExp} * DealDummy_j * PartneringExp + \boldsymbol{\beta^2 X} + \lambda + \varepsilon \quad (5)$$

In this model, j indexes the subsequent deals of the new venture, and $DealDummy_j$ is a set of indicator variables indicating future deals for slow firms. The variable $PartneringExp$ is our measure of the collaborative capabilities of the firm, and $\alpha_j$and $\alpha_j^{PartneringExp}$ are corresponding coefficients for the future deal dummies and their interactions with $PartneringExp$. In hypothesis 3, we expect that the positive effects from partnering for a slow firm will persist yet diminish into future projects, such that α_j should be positive and significant for temporally proximate deals (corresponding to low levels of j) and gradually reduce in magnitude and significance for temporally distant future deals (corresponding to higher levels of j). In hypothesis 4, we expect that these positive effects should be contingent upon the collaborative capabilities of the firm, such that $\alpha_j^{PartneringExp}$ should be positive and significant for temporally proximate deals (corresponding to low levels of j) and gradually reduce in magnitude and significance for temporally distant future deals (corresponding to higher levels of j).

Variables

Our central dependent variable of interest is *Speed Performance,* which is the average feet drilled per day for a well site. Specifically, we calculate this variable by taking the total depth of the focal well site and then dividing by the total number of drilling days needed to complete drilling there (using the drilling commencement and completion dates). (Kellogg 2011). Using this average measure helps smooth out any daily variations during the drilling process.

As noted above, one of our central explanatory variables is $Partnering$. For measuring whether firms partner or go it alone in a drilling contract, we construct *Partnering* to be equal to 1 if the focal driller enters into a partnership with another driller for the given well project, and 0 otherwise.

For our measure of firm slowness, we follow past literature (Hawk et al. 2013, Pacheco-de-Almeida et al. 2015, Hawk et al. 2021) and use a residual from a firm stage regression to construct a measure of the intrinsic speed capabilities of the firm. To do this, we use our full sample of drilling well site projects and estimate a first-stage regression using the dependent variable of the firm's drilling rate and incorporate independent variables capturing the systematic determinants of the drilling rate of the wells in our sample at the project well site level. We thus run the following OLS model using our drilling data at the project level (indexed for well w, field f, firm i, and time t):

$$\begin{aligned} DrillingRate_{w,f,t} \\ &= \beta_0 + \beta_1\, WellType_{w,f,t} + \beta_2\, ProjectSize_{w,f,t} + \beta_3\, ContractType_{w,f,t} \\ &+ \beta_4\, OilPotential_{f,t} + \beta_5\, OilDemand_t + \overrightarrow{\beta_6} FIELDDUM + \overrightarrow{\beta_7} YEARDUM + \theta_{i,\mathrm{w},t} \end{aligned} \tag{6}$$

In this regression, $DrillingRate_{w,f,t}$ is the feet per day drilling rate achieved for the well site, $WellType_{w,f,t}$ is the type of well (vertical versus directional), $ProjectSize_{w,f,t}$ is the total depth of the well site, $ContractType_{w,f,t}$ is a variable capturing whether the contract is footage, dayrate, or turnkey design, $OilPotential_{f,t}$ is the expected oil reserves in the current field, $OilDemand_{w,f,t}$ captures demand conditions at the time of the drilling and is based on monthly oil consumption data from the U.S. Energy Information Administration (EIA) in millions of barrels, 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 taking our full set of drilling projects to obtain an estimate that captures whether firms are intrinsically slow or fast at drilling, while controlling for all systematic determinants of drilling speed at the project level. Thus, all of our variables are at the project level, and we will create a lagged structure in our final measurement to capture the intrinsic slowness of the firm before entering into the focal project in our final analysis. In the regression above, we are thus decomposing the realized drilling rate of the well into a set of systematic determinants captured by the explanatory variables at the project level, and 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 and is modelled as a reflection of the intrinsic speed capabilities of the firm. 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 site. If the residual is negative, it captures the degree to which the firm realizes slower than systematic expected drilling rate for the given well site. This residual, then, becomes the basis for our measurement of the intrinsic speed capabilities of the firm: we take this residual and standardize them within each field, product, year subgroup. We take the average of the firm's residuals for each firm year and collapse to the firm year level. We reverse code this measure to capture the intrinsic slowness of the firm. We then map this measure onto a firm year panel by taking a moving average over a three-year window lagged by one year (i.e., calculated for the prior three years) and assume neutral speed for years with no speed information. The resulting measure, $Slowness$ thus becomes a time variant measure of the intrinsic speed capabilities of the firm with a lagged structure to facilitate identification.

For our measure of collaboration capabilities of the firm, we rely on partnering experience as a proxy given that accumulated experience with alliances serves is a critical input for the development of firm abilities at managing the collaborative experience implicit in an alliance (Eisenhardt and Martin 2000, Kale et al. 2002). Accordingly, we use the variable $PartneringExp$, constructed as the number of partnerships in which the focal driller has previously engaged.

We then incorporate numerous control variables to account for other determinants of firm speed performance to address concerns of omitted variable bias. We include a measure of firm size in case larger and smaller firms have systematic differences in speed performance (Chen and Hambrick 1995). $Firm\ Size$ is proxied by the number of rigs in the focal driller's fleet. Younger firms could also have systematically different speed performance than older firms (Shrader, Oviatt, and McDougall 2000); and thus $Firm\ Age$ is constructed as the number of years since the focal drilling firm's founding year. Firms with more advanced technology can perform their tasks faster; and thus we construct $Firm\ Rig\ Tech$ as the focal driller's technology level, measured as the average of its rig horsepower. Relational experience between the supplier driller and its client producer can also impact the driller's performance because there is significant knowledge sharing and coordination between the two parties during well drilling; we thus control for $Prior\ Client\ Ties$, which is measured the number of previous projects that the supplier-client pair have worked on together. Firms with more previous experience with particular types of products may also realize greater speed performance (Wheelwright and Clark 1992); and thus we control for this effect with $Project\ Related\ Experience$, which in our context is constructed as the focal driller's prior cumulative number of similar well types drilled. Speed performance may be systematically different for different levels of complexity across wells (Kellogg 2011); and thus we control for this variation with $Project\ Specification$, which measures the technical complexity of a given well site. Greater levels of rivalry and competition may also systematically affect realized speed performance (Chen and Hambrick 1995); and thus we control for these competitive effects with $Number\ of\ Rivals$, which is measured as counting the number of incumbent rival drillers in the same oil field. We finally control for $Industry\ Health$, constructed as the natural log of the current real oil price level obtained monthly from U.S. Energy Information Administration (EIA), because demand conditions and overall industry health may also influence firm performance (Mascarenhas and Aaker 1989). In our context, stronger oil demand incentivizes drillers to complete wells and begin oil production faster. Finally, for our analyses on persistent effects on subsequent deals, we control for $FocalDealPartnering$ which captures whether the focal future deal of interest involves of partnership or not.

For our Heckman correction to account for governance endogeneity related to firms' decisions to pursue projects in collaboration versus autonomously, we include two variables in a first stage selection equation that serve as exclusion restrictions (Castañer et al. 2014): Our first variable is $Demand\ Uncertainty$, a measure of the demand uncertainty of oil in the market as measured by the standard deviation of US monthly oil demand over the past five years prior to the focal project well. For our second variable, we use $Field\ Market\ Size$, which reflects the expected oil potential of a given field. The intuition behind these two variables used as exclusion restrictions in the first stage is as follows. Both the level of demand uncertainty and the field market size are likely to affect the decision of firms to partner versus go it alone. Greater levels of uncertainty may make contracting with a partner unpredictable and risky, leading to higher risk of holdup due to the locational specificity of transporting and locating drilling equipment for a particular field. This greater risk of hold up is likely to make going it alone more favorable than partnering. Similarly, greater field potential may lead the focal firm to be more likely to bring on a partner due to the scale of the project. However, both demand uncertainty and field market size are exogenous to drilling performance, as greater variances in demand or scale are conceptually independent from realized speed, and thus have an ambiguous effect on the feet drilled per day. It is also worth noting that the contracted drillers do not capture any of the revenue generated from the oil produced from the well because the producer who is the owner of the well captures all the revenue generated there, and thus their incentives to drill faster should not vary based on the well site's oil potential.

Identification Strategy

Our empirical objective is to estimate the effect of the decision to partner versus go it alone on the subsequent realized speed performance of the firm in a given project. We also wished to explore if this relationship differs based on the slowness, or lack of intrinsic speed capabilities of the focal firm. To accomplish this goal, we needed to select an analytic strategy that allows us to deal with several challenges such as omitted variable bias, strategy selection effects, simultaneity and reverse causality.

Accordingly, we elected to pursue a variety of identification strategies that allows us as a set to cope with the empirical challenges highlighted above. Our first identification strategy is regression, also referred to as identification by adjustment. In this approach, our goal is to obtain a consistent estimate of partnering on speed performance by controlling for all other potential factors that influence realized speed performance in a vector of control variables. If we are able to fully specify a set of control variables, we can partial out the effects of these other variables, minimize omitted variable bias, and obtain a consistent estimate of our focal relationship of interest. When building our control structure, an important consideration is that the decision to partner versus go it alone is likely to be chosen by the firm rather than randomly assigned. This selection process creates an unobserved interdependency between the decision to partner and realized speed performance. To address this potential influence of strategy self-selection effects and account for unobserved counterfactuals of firms' partnering versus go-it-alone decisions, we follow past literature (e.g., Masten 1993, Shaver 1998, Leiblein et al. 2002, Brouthers, Brouthers, and Werner 2003, Hamilton and Nickerson 2003, Castañer et al. 2014) and use a Heckman-type correction where we model the selection equation as a first stage and control for strategy self-selection effects via inclusion of the inverse mills ratio as an additional control variable in the second stage performance regression. An attractive feature of a Heckman-type treatment effect correction is that it treats strategy self-selection as a type of omitted variable bias and controls for it via the inclusion of the inverse mills ratio. Regarding concerns about reverse causality and/or simultaneity, our measurement of partnering is lagged relative to the subsequent speed performance realized in the project, and this temporal structure reduces these concerns. We use standard errors clustered by focal drillers in our models to adjust for correlation across the error term for multiple observations for a given firm. To further account for potential omitted time invariant firm heterogeneity, we allow the intercept to be random in the random coefficient models which acts as a random firm effect. As an additional check, we estimated firm fixed effects specifications and found results consistent with our main results. We further attempt to minimize omitted variable bias or other endogeneity concerns via a series of robustness checks on variable construction and set of control variables included in the regressions (results available from the authors).

In our second approach to identification, we take an alternative approach to address non-random assignment of the treatment. As discussed above, a central consideration in our empirics is that the decision to partner versus go it alone is not randomly assigned across firms, creating a challenge for establishing causal inference in the effect of partnering on speed performance. To further address this challenge, our second identification strategy is treatment effect analysis, or identification by balancing. In this approach, we attempt to approximate the experimental ideal by creating a treatment group and a control group that are as comparable as possible but differ only in that they receive the treatment of interest in our study, which in our case is the decision to partner rather than go it alone. This method thus allows us to compare like with like by balancing the treatment group and control group using a set of variables that shape the decision to partner versus go it alone. To construct a properly balanced treatment group and control group, we ran a first stage selection model and used propensity score matching (using the teffects psmatch suite in Stata) as well as propensity score inverse probability weighting (using the teffects ipw suite in Stata). The two treatment effects methods approach balancing differently, where propensity score matching balances the treatment group and control group via matching using propensity scores, whereas inverse probability weighting uses propensity scores to weight different observations in the treatment group and control group to achieve balancing between the two groups. A second stage regression is then run using the balanced treatment group and control group, yielding an estimate of the effect of partnering on subsequent speed performance. This estimate of the average treatment effect of partnering on speed performance, if similar to our main results, would provide further reassurance that we are adequately accounting for unobserved interdependencies between partnering and speed performance and obtaining a consistent estimate of the causal effect of interest.

We then pursue a third identification strategy called doubly robust estimation. This approach combines elements of our first approach (regression, or identification by adjustment) with our second approach (treatment effect analysis, or identification by balancing). Here, we continue to use our balanced treatment group and control group obtained in our second approach using inverse probability weighting, but we also control for the vector of variables in the second stage that may affect variance of the outcome variable speed performance. An attractive feature of this approach is a doubly robust property, where a consistent estimate is achieved if either the selection model or the outcome model is correctly specified (Morgan and Winship 2014). In other words, if the selection equation is incorrect but the outcome model is correct, or alternatively if the selection model is correct but the outcome model is incorrect, we still obtain a consistent estimate as long as one of the two equations is correctly specified. If the resulting estimate is similar to the estimates from our other two identification strategies, we obtain further reassurance that our results as a whole represent a consistent estimate of the impact of partnering on speed performance while accounting for the empirical challenges articulated above.

RESULTS

We begin with descriptive statistics and a correlation table presented in Table 1. We first checked variance inflation factors (VIFs) to see if multicollinearity is problematic. All VIFs were below 10 with the mean VIF of 2.19 and a max of 3.29, suggesting multicollinearity is at acceptable levels. Looking at the correlation matrix in Table 1, we can see some initial evidence that partnering is negatively correlated with speed performance, suggesting that partnering may generally impair speed performance rather than enhance it. We also see intrinsically slow firms have slower speed performance, as expected. Interestingly, larger firms tend to have slower speed performance, perhaps reflecting greater levels of firm inertia, and older firms tend to have greater speed performance, which may reflect further development of routines and progress alone learning curves. Firms with prior client ties, and those having greater rig technology and related product experience all tend to have greater speed performance, and greater competition in the form of rivals as well as better demand conditions captured by the $Industry\ Health$ variable all are associated with greater levels of speed performance. Interestingly, more complex well sites, captured by the $Project\ Specification$ variable, are associated with slower speed performance, suggesting that technical challenges impede speed performance as expected.

In Table 2, we first present results for the baseline model in equation (1) in column 1 where the dependent variable is $Speed\ Performance$ and our main predictor is $Partnering$, which is the dummy representing the choice of whether to partner or go it alone. This baseline linear model is fitted with OLS with standard errors clustered by firm. Interestingly, the estimated coefficient on partnering is negative and insignificant, suggesting that there is an indeterminant relationship between partnering and speed performance.

We next present results that examine the role of firm heterogeneity in the partnering – speed performance relationship in order to test our theory. To do this, we augment the baseline linear model as depicted in Equation (2) by incorporating a Heckman correction to account for non-random assignment of the partnership treatment, and we also adjust our model to use a random coefficient RCM specification to allow for firm heterogeneity in the marginal effect of partnering. In column 2, we present the selection model. This model is fitted using a probit, and our two exclusion restriction variables ($Demand\ Uncertainty$ and $Field\ Market\ Size$) are included. In column 2, both of these variables are significant determinants of the choice to partner or go it alone: $Demand\ Uncertainty$ has a negative and significant coefficient, suggesting firms are more likely to go it alone in regimes of high demand uncertainty, likely due to the difficulty and costs of contracting in the presence of the high location specificity of rig location and transportation decisions, leading firms to prefer to go it alone. $Field\ Market\ Size$ has a positive and significant coefficient, suggesting firms operating on a huge project are, all else equal, more likely to partner to take on the scale of the project. We checked whether these two variables are correlated with the second stage speed performance dependent variable, and we confirmed that they are unrelated to the second stage dependent variable (r = -.14 and .12, respectively; p values of p=.154 and p=.107). The results also indicate that larger firms, firms with prior client ties, and firms with more related experience are more likely to go it alone (perhaps due to their greater drilling asset base and familiarity with a particular client or project type), and firms with more partnering experience, firms with drilling in well sites with greater complexity, and firms drilling in industry conditions with greater demand are all more likely to partner rather than go it alone.

In addition, an important included variable of the selection model in Column 2 is firm $Slowness$. As discussed in the theory section, Hawk et al. (2021) predicted and showed that slow firms are more likely to partner than to go it alone, suggesting that $Slowness$ is an important determinant in the decision to partner or go it alone and should be included. In our results, the coefficient on $Slowness$ is positive and significant, indicating that slow firms are more likely to partner than go it alone, thus replicating the findings of Hawk et al. (2021) in our context.

In column 3, we present the results corresponding to Equation (2), our random coefficient model specification with a Heckman-type correction predicting the determinants of speed performance. The Inverse Mills Ratio is positive and significant, suggesting that positive self-selection is occurring, which means that the coefficient estimates would have been upward biased without this correction. Similar to the baseline OLS results, we find an estimated average coefficient on $Partnering$ that is negative though insignificant at conventional levels (p = .153).

We next turn to testing hypothesis 1 where we predicted that the effect of partnering on speed performance should vary significantly across firms. Looking at column 3, the standard deviation component of the random coefficient estimate on partnering is presented as "S.D.(Partnering)" in the table. Estimation results indicate a significant standard deviation of the Partnering random coefficient, thus supporting Hypothesis 1. This finding suggests firm heterogeneity matters a great deal in the relationship between partnering and speed performance. Given that the mean effect is insignificant but the standard deviation is significant, the distribution of the random coefficient estimate suggests it is likely some firms have positive firm specific marginal effects and other firms have negative firm specific marginal effects. This insight suggests partnering is likely to be speed performance enhancing for some firms and speed performance destroying for other firms.

To gain further insights into the nature and importance of firm heterogeneity in the speed performance implications of partnering versus going it alone, we obtain firm specific marginal effect predictions from the random coefficient estimation and we graphically display a few of them in a centipede plot in Figure 2. By graphically showing a sample of firm-specific marginal effects, we can obtain some firm-specific insights and enrich our large sample econometric results to offer some initial evidence of which firms may be enhancing speed performance and which firms may be destroying speed performance by partnering versus going it alone (see Figure 2). Several firms like Atlas Drilling, Eagle Rock Drilling, Helmrich & Payne, Independence Drilling, Nabors Industries, O-Ryan Drilling, Patterson and Wisco Moran all had positive speed performance implications of partnering: their firm specific marginal effects of partnering on speed performance are all positive and significant with 95% confidence intervals that do not intersect 0. These findings suggest that these firms on the margin could use partnering as an acceleration strategy to enhance their speed performance. In contrast to these results, firms like Bison Drilling, Hazelett Drilling, MCG Drilling, Norton Energy, Patriot Drilling, and Schlumberger all have negative speed performance implications of partnering: their firm specific marginal effects are all negative and significant. These firm specific insights highlight the importance of firm heterogeneity in the relationship between partnering and speed performance, further supporting Hypothesis 1: the marginal effect of partnering significantly varies across firms.

Our next step in the analysis is to explore why the relationship between partnering and speed performance varies across firms. Specifically, we predict in hypothesis 2 that partnering should be speed performance enhancing for slower firms. Estimation results corresponding to equation (4) appear in Table 2's column 4. In this model, we introduce the interaction between $Slowness$ and $Partnering$. We find a positive and significance coefficient on this interaction term ($p = .018$), thus supporting hypothesis 2. This result supports our theoretical expectation in hypothesis 2 that partnering is enhancing to the speed performance of slower firms. Our results suggest that, for a firm having intrinsic slowness of one standard deviation above the sample mean, partnering boosts speed performance by over 3%. Given that the typical driller's drilling speed is about 150 feet/day, an improvement of 3% for such drillers means a drilling speed increase of about 4.5 feet/day (to about 154.5 feet/day). If a well site that is 9,000 feet deep usually takes that driller 60 days to complete, such speed improvement can translate to the driller completing that well for the client almost 2 days earlier, which can result in substantial cost savings. These results suggest that partnering can be economically meaningful for intrinsically slower firms.

We next focus on whether the effect of partnering for slow firms extends into future well site projects as predicted in hypothesis 3. Results testing these ideas are presented in Table 3. Here, we constrain the sample to subsequent projects for slow firms who partnered in the initial focal alliance. As before, we present our selection equation in column 1 and find a similar set of results as above. In column 2, we present the speed performance results with the Inverse Mills Ratio correction. As before, the Inverse Mills Ratio is positive and significant, supporting its use in our empirics. In hypothesis 3, we predicted that the benefits of partnering for slow firms will persist yet diminish in future projects. We test these predictions using the set of project deal dummies are labeled as Deal Dummies displayed in Table 3's column 2. The coefficient for the second deal indicator (labelled $SecondDeal$) is positive and significant (p=.025), suggesting that the benefits of partnering for slow firms are persisting into the next deal. Additionally, the dummy for the third deal (labelled $ThirdDeal$) continues to be positive and significant but with lower magnitude and significance (p=.058). The coefficient estimates here suggests that intrinsically slow firms partnering in the focal deal can continue to enjoy speed improvements of about 7% in their follow-up deal and 5% in their third deal, compared to their sixth and beyond deals. The coefficients on the fourth deal and fifth deals (labelled $FourthDeal$ and $FifthDeal$) are insignificant. These results suggest that the benefits of partnering for slow firms persist into the next two projects, but these effects diminish over time in both magnitude and significance, supporting our prediction in hypothesis 3.

We then turn to our theoretical expectation in hypothesis 4 that the persistence of these effects for slow firms hinges on the firms possessing collaborative capabilities. We present results testing this prediction in column 3. Here, we augment our model from column 2 by adding interactions between the deal dummies and the variable $PartneringExp$, our measure of the firm's partnering experience. The results on the set of deal dummies shows a similar pattern as in column 2. The coefficients on the $SecondDeal$ dummy and the $ThirdDeal$ dummy continue to be positive and significant with declining magnitude and significance and turn insignificant by the fourth deal. Note that the coefficients on these dummies alone represent the scenario where firms have zero partnering experience, and they all are of smaller magnitude than the results in column 2. These results suggest that benefits that slow firms enjoy from partnering do persist into future deals, but they are lower if the firm does not have collaborative capabilities. Next, interesting interpretations exist for the interaction terms between the partnering dummies and the partnering experience variable $PartneringExp$. Here, the interaction terms between $PartneringExp$ and the second deal and third deal dummies are both significant, and they reduce in magnitude and significance into the future and turn insignificant by the fourth project. The coefficient estimates here suggest that for intrinsically slow firms possessing high collaboration capabilities (where its partnering experience is at least one standard deviation above the sample mean), those partnering in the focal deal can continue to enjoy speed improvements of about 5% in their follow-up deal and 3% in their third deal, compared to their sixth and beyond deals. These results suggest that greater collaborative experience amplifies the positive effect of partnering for slow firms into future deals, supporting hypothesis 4, and these benefits diminish over time as before and turn insignificant by the fourth project.

Additional Analysis: Treatment Effect Analysis

In the next stage of our empirical analysis, we apply alternative identification strategies as discussed in the section above. For our treatment effect analyses, we use three complementary approaches: (1) propensity score matching and (2) inverse probability weighting as initial lenses to estimate the average treatment effect, and (3) doubly robust estimation, which combines the inverse probability weighting with controls in the second stage regression. We then compare our estimates from the three different treatment effect analyses methods with our main results in Table 2. If the full set of results reinforce each other in the main, we have reassurances that our econometrics as a whole are providing a compelling estimate of the impact of partnering on speed performance.

We present the treatment effects analyses results in Table 4. Model 1 presents the results for propensity score matching (obtained using the stata suite teffects psmatch), and Model 2 shows the results for inverse probability weighting (obtained using the stata suite teffects ipw). Model 3 then presents the results for doubly robust estimation, which uses the balanced treatment group and control group from inverse probability weighting but also includes the same set of covariates as controls in the second stage regression (obtained using the stata suite teffects ipwra). The first panel across the three models using the sample of drillers indicates very similar estimates of the average treatment effect of partnering on speed performance. Across all methods, the average treatment effect is insignificant (the different in speed performance all have p values greater than .10). These results are consistent with our main results:

partnering versus going it alone on average across all firms in the sample has an indeterminant relationship with speed performance.

We next turn to the panel below where we constrain the sample to intrinsically slow firms, i.e., firms where $Slowness > 0$. Across the three models, we see very similar estimates of the average treatment effect of partnering on speed performance, and these estimates are similar to our main results. Across the three methods, the average treatment effect is positive and significant (using propensity score matching, intrinsically slow firms are 16.264 feet/day faster when partnering versus go it alone with a p value of .011; using inverse probability weighting, the difference is 13.579 feet/day faster with a p value of .007; using doubly robust estimation, the difference is 11.585 feet/day faster with a p value of .006).

Additional Analysis: Capabilities of the Partner Firm

An additional possibility is that the capabilities of the partner firm are an important facet of capability acquisition that deserve examination. Given that we believe slow firms can potentially internally develop their own capabilities from partnerships and have better speed performance in future deals due to capability acquisition from the partner firm, we should expect that our results for the persistence of our effects into future deals should be strengthened in the scenario where an intrinsically slow firm partners with an intrinsically fast partner firm.

We conduct additional analysis to explore this possibility, and we present these results in Table 5. Here, we constrain our sample to the scenario where slow firms partner with fast partners in the initial project. Comparing these persistence results with our main persistence results presented in Table 3 (which capture slow firms partnering more generally rather than slow firms partnering with fast partners), we find a very similar pattern of results. We present our selection equation in Column 1, and we present our speed performance results with the Heckman-type correction in Columns 2 and 3. Looking at the results in Column 2, the coefficients on the $SecondDeal$ and $ThirdDeal$ dummies continue to be positive and significant (p=.021 and p=.050, respectively), and, interestingly, the coefficient on the $FourthDeal$ dummy is now significant (p=.077). Additionally, the size of these coefficients is larger here than in our main results. It appears that when slow firms partner with a fast partner firm, the benefits extend further into future projects (until the fourth deal) and the future benefits are larger. We then present the interaction results with collaborative experience in Column 3 and find a similar pattern. The coefficients on the deal dummies alone are larger than in Table 3 and stay significant until the $FourthDeal$ dummy rather than the $ThirdDeal$ dummy. Additionally, the interaction terms are also larger. These results broadly suggest that our theoretical expectations in Hypotheses 3 and 4 hold stronger for when slow firms partner with fast partner firms: the benefits they enjoy in future projects are larger and persist longer into future deals. Note that we did also consider what happens when intrinsically slow firms partner with other slow firms. In this additional check (available by request from the authors), we constrain our sample to the scenario where slow firms partner with other slow firms in the initial project. In this scenario, we find that the performance benefit of partnering persists only to the next deal, but not beyond.

Other Robustness Checks

We conducted additional robustness checks to provide further confidence in our results (results available from the authors). First, we tried an alternative measure of speed of project completion. In our main analysis, we measured speed as our dependent variable in the second stage based on feet drilled per day, where a higher value denotes faster speed. Alternatively, we measured our dependent variable based on the number of days from drilling start to completion for a given well site; here, lower values mean faster speed. By using this alternative outcome, we find results consistent with our main results. We also tried an alternative measure of our main moderator 'slowness' based on the residual drilling speed by using rig technology instead as measured by its horsepower. To keep our coefficient interpretations consistent, we again reverse code this measure such that higher values means being slower. Using this alternative predictor, we still find the moderation effect to be consistent with our prediction.

We also tested the robustness of our results by adjusting the functional form. We reran our analyses using firm fixed effects rather than using the random coefficient specification, and our results were similar to the main results. We also included additional controls by examining whether the characteristics of the partner driller affect our main analyses. We ran a two-stage instrumental variable model with the Heckman-type correction and included the additional sets of partner driller controls in the second stage for the partnering sample. Specifically, the controls for the partner's characteristics included the partner's size, age, specializations, rig technology, and product related experiences. To account for our predictor 'slowness' being significantly correlated with firm characteristics that would bias the interaction effect of slowness, we also included the additional controls in the second stage for the interaction effects of firm characteristics of size and age with partnering. When we included these additional controls, our main results remained robust.

We also tested the robustness of our treatment effects analyses by considering all possible random assignments between our treatment and controls groups. To do this, we ran a randomization inference test to allow our 'partnering' variable to be assigned randomly, which essentially allows us to stipulate the counterfactual, or what we would have observed among the control group (those not partnering) had been treated (if they partnered), or among the treated units had they not been treated. Consistent with our predictions, we found that the effect of partnering for slow drillers has a positive and significant effect on their speed performance, where the randomization inference p-value (0.021) is derived using 1,000 draws based on firm-level randomization.

Finally, when we checked for influential outliers, we found that drilling speed was substantially higher for shallow wells (those less than 1000 ft in depth). Such findings make intuitive sense because shallow well sites are less complex and thus easier to drill compared to deeper well sites that involve more varied rock stratifications – these shallow wells can often be completed in less than one week. Although these shallow wells constitute only about 7% of the overall population, it is possible that including these wells can bias our results. To address this concern, we reran our analyses for a subsample of well sites that are at least 8000 feet deep – such wells there are essentially impossible to drill in less than one week. Even using this subsample of more complex projects, our main findings and interpretations remained robust.

DISCUSSION

Contributions and Implications

In this study, we examine the impact of partnering versus going it alone on the speed performance of firms. We advance the premise that firm heterogeneity may determine whether alliances are speed performance enhancing or are detrimental to firms. We expect that the effect of partnering on speed performance significantly varies across firms due to the firm-specific nature of firm resources and capabilities to execute alliances. We then focus on one particular form of firm heterogeneity, intrinsic speed capabilities, that may explain whether partnering may be speed performance enhancing or detrimental. Our basic intuition is that partnering is more likely to be speed performance enhancing for intrinsically slow firms, and we identify contingencies shaping the speed benefits that slow firms enjoy from alliances. Using a variety of methods including random coefficient models with Heckman-type corrections to account for strategy self-selection and an assortment of additional treatment effects analysis methods such as propensity score matching, inverse probability weighting, and doubly robust estimation, we find a set of econometric results that are supportive of our theoretical arguments. Additionally, our results also serve as a cautionary tale to managers to be careful with alliances and selectively apply them, showing that partnerships on average have an indeterminant impact on speed performance, and they only serve as an acceleration strategy for particular firms, specifically slow firms with abilities to absorb and learn. Of course, firms may be pursuing partnerships for other motivations, so our results also indicate they may need to trade speed performance to accomplish those goals.

Our study has a number of contributions for the literatures on alliances as well as competence-based perspectives in this domain as well as more generally. First, we contribute to the literature on alliances and the different perspectives that have been offered on the speed implications of alliances. There has been a long-standing emphasis in the practitioner literature that speed is a potential benefit from partnering, but there has also been a rich academic literature emphasizing the potential downsides of alliances stemming from partner coordination and conflict that might impair speed. Given this tension, we began the study by suggesting that whether alliances enhance speed as portrayed in various practitioner writings over the decades is, in fact, theoretically ambiguous and likely not universally true. We also suggested the need to consider relevant contingencies that inform this tension as well as shape the speed benefits that firms potentially enjoy from alliances, and our theory emphasizes the role of speed capabilities in particular. We thus contribute to the literature by examining and contributing to our understanding of the understudied link between partnering and speed performance, thereby offering new insights on time-related aspects of alliances (Oliveira, Lumineau, and Ariño 2023). Our results suggest that firm heterogeneity plays a prominent role in determining whether a partnership will speed up or slow down a firm. Slow firms in particular can enhance their speed performance by partnering, whereas fast firms can move quicker by going it alone. Additionally, we show how the benefits that slow firms enjoy from partnering can extend into future projects, but these future benefits hinge on the collaborative capabilities of the firm. These results thus add to our understanding of the temporal dynamics of using partnerships to enhance speed performance over time: partnerships have speed implications not only for the current project but for future projects as well. This finding suggests that firms are internalizing the capabilities of their partners to enhance their speed performance, rather than only accessing these capabilities for a focal project (e.g., Grant and Baden-Fuller 2004). Since our arguments and evidence highlight the importance of the firm's absorptive capacity in acquiring speed capabilities that might enhance future projects, our research also identifies another important benefit that firms can derive from their alliance experiences. More broadly, given that the alliance literature also often mentioned speed as one of many strategic rationales for partnering, we also offer an empirical contribution to this literature by examining the speed performance implications of alliances in an interesting empirical context in which speed matters. Measuring the performance implications of alliances has been a vexing challenge for empirical research in this literature (Ariño 2003), and we offer firm speed as another potential benefit of collaborations that might be further investigated beyond the partner vs. go it alone choice that is our focus. For instance, future research might study how various facets of alliance deal-making, design, and execution might have a bearing on speed. Research along these lines might identify additional, important contingencies that enable firms to enhance their speed performance via alliances.

Second, we contribute to the literature on the Resource Based View (RBV) by emphasizing the importance of firm heterogeneity, the central focus of the RBV, in the temporal consequences of firms' selection of expansion modes to organize and implement economic activity. Our study focuses on one particular method of organizing projects, partnerships versus going it alone, and considers how this organizational decision can influence a particular performance metric, speed performance. Our finding shows that firm heterogeneity plays a central role in this temporal aspect of competition: we highlight a particular set of firm capabilities, intrinsic speed capabilities, as a central determinant of this differential outcome across firms, and we demonstrate these benefits may extend over time into future deals. It would be valuable in future studies to consider how other resources and capabilities (e.g. related to marketing intangibles, distribution reach, environmental capabilities in manufacturing, disruptive versus non-disruptive know-how, artificial intelligence, human resources, etc.) potentially affect the speed benefits of alliances and how these potential benefits extend into future projects. Moreover, it might be that other resources and capabilities also have an important bearing on the speed costs of alliances (e.g., perhaps due to their tacit nature or technical complexity), as well as the degree to which time compression diseconomies and asset accumulation lags feature in autonomous projects. Research in directions such as these can offer a more complete picture of how firm resources and capabilities affect the net speed benefits of alliances and the tradeoffs firms encounter when partnering versus going it alone.

Third, we also make contributions to the corporate strategy literature. Our study focuses on choices between expansion modes, specifically the decision to partner versus go it alone, and the speed performance implications of this decision. A rich literature has examined the tradeoffs between different modes of corporate expansion such as alliances versus acquisitions, but the tradeoffs between alliances versus organic growth has received less attention. The relative scarcity of research in this domain reflects data collection challenges that we are able to overcome through our study of oil and gas drilling projects. We thus contribute to this literature and extend it by focusing on the speed dynamics and outcomes of these decisions over time. In addition, we introduce the notion of intrinsic speed capabilities, an idea developed in the competitive strategy literature, to the corporate strategy literature and highlight how the intrinsic capabilities of firms to move quickly affects the cost benefit tradeoffs of alliances versus organic growth. Our study thus adds to our understanding of the temporal dynamics of expansion mode choices and emphasizes capability based firm heterogeneity in these dynamics, reinforcing the importance of firm differences in corporate strategy decisions. Given that our focus has been on the margin of partnering versus going it alone, future research might also investigate the speed performance implications of other ways of organizing activities, including mergers and acquisitions (e.g., Capron and Mitchell 2012). There are additional ways of sourcing capabilities and collaborating with other organizations that might also be addressed in future research on the speed performance implications of different ways of organizing economic activities (e.g., licensing of technologies, overseas joint ventures, cross-sector partnerships, multi-firm consortia, etc.).

Fourth, our study also has implications for the competitive strategy literature by illustrating how partnering may be a valuable vehicle for firms with capability deficiencies. The resource-based view has long emphasized how a variety of firm resources or capabilities can drive competitive advantage (e.g., Barney 1991), and an important component of this logic is to consider what strategies firms with resource or capability deficiencies can pursue to mitigate their limitations and compete with other, more capable firms (e.g., Barney 1999, Ahuja 2000, Berchicci, Dowell, and King 2012, 2017, Boyacıoğlu, Özdemir, and Karim 2024, Kim Forthcoming). Our study illustrates how alliances may be a way for firms with deficiencies in speed capabilities to speed up their operations, which in turn may lead to future project opportunities or better internal capability development. Future research could examine other performance outcomes of slow firms electing to do partnerships rather than going it alone, such as obtaining more attractive project opportunities or realizing greater learning and development of their own capabilities.

Limitations and Future Research Directions

Our study has several limitations that extensions to our research could address. First, we only focus on one industry, onshore oil and gas drilling, raising questions about the generalizability of our results. Oil and gas drilling is an attractive setting for our purposes since speed of drilling is a very important performance metric for firms in the industry (e.g., Kellogg, 2011). It may be the case that competition in some industries may be more speed focused in how firms compete, whereas other industries may be less time sensitive. Future research could also explore appropriate partnering speed performance metrics in high technology settings (e.g., semiconductors, pharmaceuticals, etc.) where increased technological complexity may in fact make firm heterogeneity an even more important factor in the speed performance implications of partnering.

Second, we focus on the perspective of the focal driller in our theory and our empirics. We do conduct supplementary analyses on the capability endowment of the partner firms and conduct robustness checks with the inclusion of partner firm characteristics variables, but it might also be that there are other motivations besides speed that give rise to potential bargaining dynamics between firms that also drive partner decisions. Theoretically, from the partner firm's perspective, there are likely to be a variety of considerations that may drive the decision to partner potentially related to growth and market access, access to other capabilities, risk sharing, utilization of capacity, etc. Future work could therefore further explore the perspective of the partner firm and the bargaining dynamics between alliance partners that may determine how firms trade for speed in their partnerships and motivate fast partners to allow slow firms to access their capabilities and acquire them to enhance their speed in future projects. Such research could examine the terms of these partnerships and the specifics of alliance implementation.

Third, we focus only on one speed-based performance metric, speed performance as measured by feet drilled per day. In supplemental analyses we consider project completion times, but speed could be measured in ways that adjust for potential impairment in quality or safety that we do not observe. There may be other speed performance-based metrics that could be constructed that may account for quality heterogeneity or environmental performance and enable the exploration of potential tradeoffs between speed and lower quality or safety. Future research could collect environmental or quality related metrics to explore these potential contingencies. It might also be that there are other speed-based performance metrics that could be relevant for firm competition and interesting to study such as the speed of adaptation in operations or the speed of redeployment from one site to another. The ability to compete with speed is likely to be multifaceted and involve the temporal dynamics of numerous activities throughout the value chain. Future research could focus on other time-based performance metrics located in these different activities such as speed of responsiveness, speed to market, the rate of learning and innovation, and other temporal competitive considerations. Research in such directions would be valuable to build upon our study joining the competitive strategy research on speed and firms' heterogeneous capabilities with the corporate strategy research on alternative expansion modes and on how partnerships compare with other means of organizing economic activity.

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Figure 1: Centipede plot depicting firm specific marginal effects of partnering versus go it alone on speed performance

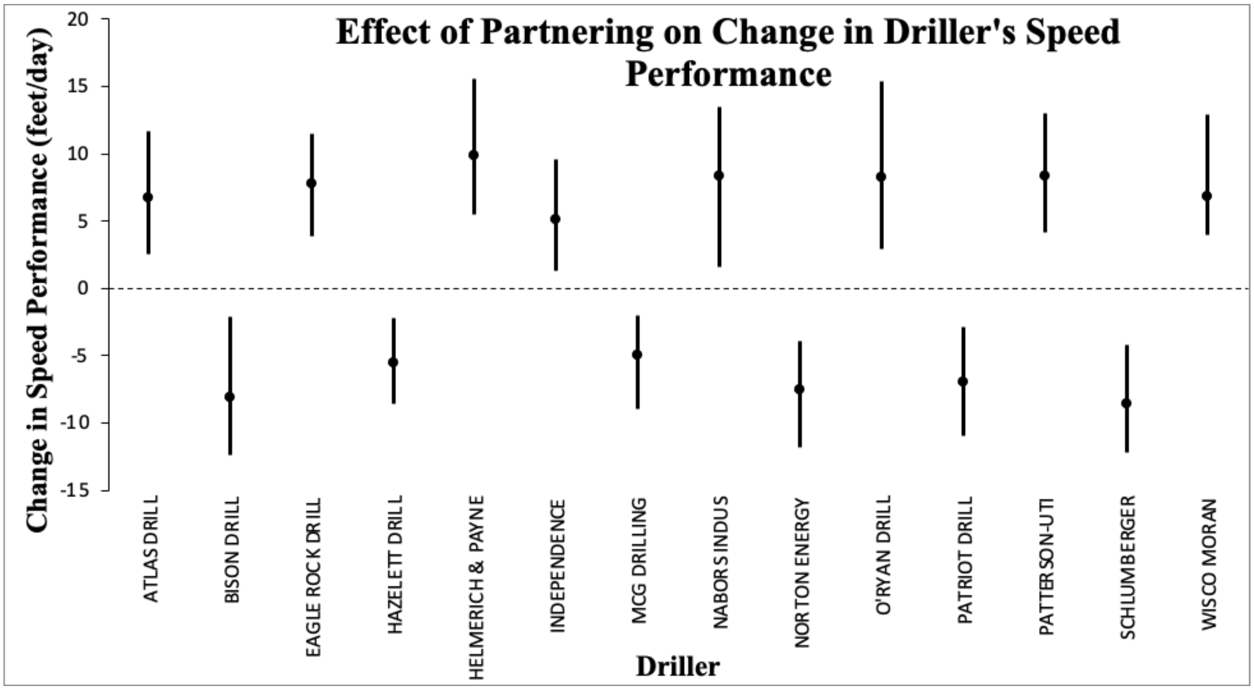

Table 1. Descriptive statistics and correlation table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Speed Performance	1.00													
2. Partnering	-0.32	1.00												
3. Slowness	-0.29	0.18	1.00											
4. Partnering Experience	0.25	0.16	-0.04	1.00										
5. Size	-0.07	-0.13	0.13	0.15	1.00									
6. Age	0.08	-0.09	-0.18	0.13	0.21	1.00								
7. Rig Tech	0.39	-0.05	-0.15	0.07	0.03	0.06	1.00							
8. Prior Client Ties	0.13	0.33	-0.19	0.06	0.27	0.44	0.04	1.00						
9. Project Related Exp	0.15	-0.24	-0.12	0.12	0.21	0.32	0.02	0.38	1.00					
10. Project Specifications	-0.15	0.17	0.10	0.09	0.02	0.02	0.46	0.13	0.23	1.00				
11. Number of Rivals	0.09	0.12	-0.06	0.04	0.23	0.34	0.11	0.16	0.08	0.02	1.00			
12. Industry Health	0.16	0.15	-0.08	-0.01	0.06	0.03	-0.09	0.12	0.11	-0.15	0.11	1.00		
13. Demand Uncertainty	-0.14	-0.43	-0.05	0.02	-0.03	0.01	0.07	0.07	0.02	-0.17	0.01	-0.33	1.00	
14. Field Market Size	0.12	0.36	-0.06	-0.03	0.08	0.07	-0.11	0.13	-0.05	-0.12	0.23	0.04	-0.09	1.00
Mean	149.2	0.31	0.62	10.18	12.62	10.45	929.35	8.25	18.16	6.23	8.61	1.38	4.68	7.05
S.D.	31.5	0.19	3.86	4.83	5.36	4.22	298.32	3.09	8.37	2.15	4.53	0.51	2.87	3.27
VIF (mean VIF = 2.19)	1.43	1.20	1.92	2.56	1.89	2.57	1.22	3.58	2.16	3.29	2.16	1.61	2.13	2.95

Table 2: Random Coefficient Model Estimation Results of Partnering on Speed Performance

	1. Speed Performance (OLS)		2. Partnering Choice (Probit)		3. Speed Performance (RCM)		4. Speed Performance (RCM)	
Constant	18.275	*(.120)*	0.168	*(.286)*	8.382	*(.186)*	7.063	*(.196)*
	(11.767)		(.158)		(6.341)		(5.463)	
Size	-5.366	*(.176)*	-0.449	*(.007)*	-4.517	*(.091)*	-4.042	*(.218)*
	(3.962)		(.167)		(2.672)		(3.281)	
Age	2.655	*(.128)*	-0.332	*(.126)*	2.816	*(.032)*	2.069	*(.175)*
	(1.743)		(.217)		(1.315)		(1.526)	
RigTech	7.828	*(.036)*	-0.144	*(.363)*	7.217	*(.034)*	6.128	*(.052)*
	(3.741)		(.159)		(3.411)		(3.155)	
PriorClientTies	2.585	*(.078)*	-0.384	*(.038)*	1.917	*(.087)*	1.947	*(.113)*
	(1.467)		(.185)		(1.118)		(1.228)	
ProjRelExp	4.782	*(.024)*	-0.296	*(.029)*	4.315	*(.033)*	3.794	*(.039)*
	(2.124)		(.135)		(2.028)		(1.838)	
ProjSpecification	-2.962	*(.053)*	0.537	*(.027)*	-1.127	*(.082)*	-2.333	*(.073)*
	(1.528)		(.243)		(.647)		(1.299)	
NumRivals	6.741	*(.133)*	0.247	*(.176)*	5.981	*(.071)*	5.051	*(.166)*
	(4.483)		(.183)		(3.315)		(3.649)	
IndusHealth	7.897	*(.013)*	0.225	*(.065)*	6.842	*(.041)*	6.147	*(.020)*
	(3.180)		(.122)		(3.346)		(2.644)	
Partnering Experience	6.699	*(.033)*	0.390	*(.023)*	3.254	*(.198)*	5.276	*(.047)*
	(3.139)		(.171)		(2.527)		(2.657)	
Slowness			0.538	*(.041)*				
			(.263)					
Demand Uncertainty			-0.848	*(.017)*				
			(.356)					
Field Market Size			0.126	*(.051)*				
			(.065)					
InverseMillsRatio					0.953	*(.024)*	0.777	*(.019)*
					(.422)		(.331)	
Predictors:								
Partnering	-3.187	*(.224)*			-2.052	*(.153)*	-3.029	*(.143)*
	(2.619)				(1.435)		(2.068)	
Slowness							-2.802	*(.032)*
							(1.305)	
Partnering X Slowness							4.527	*(.018)*
							(1.917)	
S.D.(Partnering)					1.763	*(.008)*	1.458	*(.150)*
					(.662)		(1.013)	
S.D.(Constant)					1.777	*(.012)*	1.791	*(.138)*
					(.704)		(1.209)	
S.D.(Residual)					7.044	*(.016)*	4.400	*(.111)*
					(2.928)		(2.758)	
Observations	11,572		11,572		11,572		11,572	

Notes: Using random-coefficient model with random intercept. The predictor ‘slowness’ is estimated based on three-year moving average. This measure is also lagged one year relative to the dependent variable. Standard errors clustered by firm. The *p*-values are reported in parentheses to the right of each coefficient.

Table 3: Persistence effect of 'slow' firms partnering

	1. Partnering Choice (Probit)		2. Speed Performance (OLS)		3. Speed Performance (OLS)	
Constant	0.192	*(.336)*	7.897	*(.127)*	7.661	*(.137)*
	(.200)		(5.169)		(5.143)	
Size	-0.366	*(.212)*	-1.954	*(.107)*	-1.895	*(.117)*
	(.293)		(1.213)		(1.207)	
Age	-0.259	*(.152)*	1.647	*(.161)*	1.597	*(.172)*
	(.181)		(1.174)		(1.168)	
RigTech	-0.119	*(.339)*	4.117	*(.047)*	3.994	*(.053)*
	(.125)		(2.075)		(2.064)	
PriorClientTies	-0.790	*(.019)*	1.933	*(.031)*	1.875	*(.036)*
	(.338)		(.897)		(.893)	
ProjRelExp	-0.239	*(.025)*	2.538	*(.028)*	2.462	*(.032)*
	(.107)		(1.154)		(1.149)	
ProjSpecification	0.525	*(.013)*	-4.555	*(.055)*	-4.419	*(.061)*
	(.212)		(2.369)		(2.357)	
NumRivals	0.268	*(.152)*	3.742	*(.147)*	3.630	*(.158)*
	(.187)		(2.581)		(2.568)	
IndusHealth	0.236	*(.028)*	5.148	*(.035)*	4.994	*(.040)*
	(.107)		(2.439)		(2.427)	
PartneringExp	0.395	*(.022)*	2.543	*(.029)*	2.467	*(.033)*
	(.172)		(1.162)		(1.156)	
Slowness	0.480	*(.035)*				
	(.227)					
DemandUncertainty	-0.797	*(.022)*				
	(.349)					
FieldMktSize	0.145	*(.051)*				
	(.074)					
InverseMillsRatio			0.683	*(.021)*	0.663	*(.043)*
			(.295)		(.327)	
FocalDealPartnering			-1.951	*(.150)*	-1.883	*(.156)*
			(1.356)		(1.328)	
Predictors:						
SecondDeal			10.534	*(.025)*	10.219	*(.030)*
			(4.704)		(4.710)	
ThirdDeal			8.027	*(.058)*	7.787	*(.067)*
			(4.236)		(4.245)	
FourthDeal			8.521	*(.124)*	7.882	*(.133)*
			(5.543)		(5.240)	
FifthDeal			7.167	*(.151)*	6.953	*(.169)*
			(4.982)		(5.056)	
PartnExp X SecondDeal					1.973	*(.024)*
					(.876)	
PartnExp X ThirdDeal					1.401	*(.060)*
					(.743)	
PartnExp X FourthDeal					1.462	*(.216)*
					(1.181)	
PartnExp X FifthDeal					1.692	*(.162)*
					(1.209)	
Year & Field Controls	Yes		Yes		Yes	
Observations	3,961		3,961		3,961	
R-squared	0.172		0.175		0.178	

Notes: Sample consists of only 'slow' drillers partnering, and the effect of partnering on their performance in subsequent deals (sample here excluding focal first deal). For the deal dummies, the reference case is sixth and beyond deals. Outcome is focal driller's speed performance for its subsequent well projects after allying with a partner. Standard errors clustered by firm.

Table 4: Treatment Effects Analysis for the impact of partnering on speed performance for fast and slow firms

	Model 1		Model 2		Model 3	
Outcome: Speed Performance	PSM		IPW		IPWRA	
ATE Sample: all drillers						
Treated (Partnering)	129.251	*(.133)*	127.373	*(.124)*	124.653	*(.137)*
	(85.921)		(82.764)		(83.794)	
Control (Not Partnering)	140.112	*(.126)*	136.025	*(.135)*	133.825	*(.122)*
	(91.634)		(90.983)		(86.476)	
Difference	-10.861	*(.145)*	-8.652	*(.140)*	-9.172	*(.199)*
	(7.451)		(5.860)		(7.144)	
Conditional ATE Sample						
"slow" drillers						
Treated (Partnering)	133.263	*(.009)*	131.363	*(.015)*	130.252	*(.013)*
	(50.684)		(54.228)		(52.590)	
Control (Not Partnering)	116.995	*(.015)*	117.785	*(.019)*	118.667	*(.012)*
	(48.164)		(50.106)		(47.081)	
Difference	16.264	*(.011)*	13.579	*(.007)*	11.585	*(.006)*
	(6.382)		(5.012)		(4.187)	

Note: Cases of drillers are matched using size, age, firm rig technology, product related experience, slowness, and prior client ties. The variables that are determinants of receiving the treatment of interest (partnering) are lagged by one year to ensure the variables are conceptual and/or temporal antecedents to the treatment (partnering) to further strengthen our identification. Model 1 uses propensity score matching (PSM). Model 2 uses inverse probability weighting (IPW). Model 3 uses doubly robust estimation (IPWRA). In all three models, covariates appear balanced: 1) using the overidentification test based on the Chi-squared distribution, the null hypothesis that the covariates are balanced cannot be rejected; 2) using the model-adjusted difference in means and ratio of variance between treated and untreated covariates, the differences in weighted means of the covariates are very small and the variance ratios are very close to 1.

Table 5: Persistence effect of 'slow' firms partnering with 'fast' firms

	1. Partnering Choice (Probit)		2. Speed Performance (OLS)		3. Speed Performance (OLS)	
Constant	0.165	*(.366)*	8.806	*(.161)*	8.190	*(.178)*
	(.183)		(6.284)		(6.077)	
Size	-0.385	*(.008)*	-1.109	*(.120)*	-1.107	*(.125)*
	(.144)		(.712)		(.722)	
Age	-0.272	*(.165)*	1.513	*(.015)*	1.483	*(.017)*
	(.196)		(.624)		(.618)	
RigTech	-0.126	*(.354)*	0.054	*(.220)*	0.053	*(.225)*
	(.135)		(.044)		(.043)	
PriorClientTies	-0.665	*(.031)*	0.823	*(.030)*	0.807	*(.032)*
	(.309)		(.380)		(.376)	
ProjRelExp	-0.251	*(.028)*	2.304	*(.067)*	2.098	*(.073)*
	(.114)		(1.259)		(1.169)	
ProjSpecification	0.442	*(.023)*	-3.234	*(.135)*	-3.030	*(.161)*
	(.194)		(2.163)		(2.161)	
NumRivals	0.226	*(.188)*	2.185	*(.151)*	2.021	*(.126)*
	(.171)		(1.521)		(1.319)	
IndusHealth	0.199	*(.043)*	6.897	*(.040)*	6.279	*(.047)*
	(.098)		(3.359)		(3.155)	
PartneringExperience	0.570	*(.016)*	1.821	*(.012)*	1.785	*(.013)*
	(.236)		(.722)		(.715)	
Slowness	0.542	*(.021)*				
	(.235)					
DemandUncertainty	-0.826	*(.014)*				
	(.335)					
FieldMktSize	0.122	*(.038)*				
	(.059)					
InverseMillsRatio			0.847	*(.031)*	0.830	*(.033)*
			(.392)		(.388)	
Predictors:						
SecondDeal			12.126	*(.021)*	11.787	*(.024)*
			(5.260)		(5.207)	
ThirdDeal			9.731	*(.050)*	9.360	*(.058)*
			(4.971)		(4.931)	
FourthDeal			8.701	*(.077)*	8.520	*(.074)*
			(4.914)		(4.766)	
FifthDeal			9.757	*(.154)*	9.757	*(.154)*
			(6.836)		(6.836)	
PartnExp X SecondDeal					2.087	*(.020)*
					(.896)	
PartnExp X ThirdDeal					1.586	*(.063)*
					(.854)	
PartnExp X FourthDeal					1.204	*(.087)*
					(.704)	
PartnExp X FifthDeal					1.521	*(.146)*
					(1.046)	
Year & Field Controls	Yes		Yes		Yes	
Observations	2,858		2,858		2,858	
R-squared	0.152		0.196		0.215	

Note: Sample consists of only 'slow' drillers allying with 'fast' partners, and the 'slow' drillers' subsequent deals (sample here excluding focal first deal). For the deal dummies, the reference case is sixth and beyond deals. Outcome is focal driller's speed performance for its subsequent well projects after allying with a 'fast' partner. Standard errors clustered by firm.