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TRANSFERRING KNOWLEDGE BY TRANSFERRING INDIVIDUALS: INNOVATIVE TECHNOLOGY USAGE AND ORGANIZATIONAL PERFORMANCE IN MULTI-UNIT FIRMS

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ABSTRACT

Transferring individuals who possess relevant knowledge from one organizational unit to another – a form of resource redeployment – may help to overcome impediments to knowledge transfer. Despite the promise of this mechanism, which often occurs through intra-firm geographic mobility, relatively little research has examined how the knowledge and expertise of individuals interacts with the organizational resources of the units to which individuals move. This study examines whether intra-firm geographic mobility improves organizational performance by providing a conduit for the transfer of knowledge, while accounting for the interaction between individual knowledge and factors at the organization-unit level of analysis. We analyze the performance effects of the transfer of engineers who have expertise in innovative process technologies. The results from a large multinational company show that the innovative process technology-related expertise of an individual engineer who moves to a new organizational unit is positively associated with the performance of that unit, suggesting that intra-firm geographic mobility improves organizational performance by providing a conduit for the transfer of knowledge. The results also show that the technology-related knowledge of engineers is a substitute for organization-level factors when a unit uses only technologies with which it is already familiar, whereas the technology-related knowledge of engineers is a complement to organization-level factors when units introduce new technologies. Thus, individuals who bring novel expertise to their organizational units through intra-firm mobility may be important vehicles for organizational learning and building new competences, helping to diffuse best practices.

Keywords: knowledge transfer, resource redeployment, strategic human capital, microfoundations, organizational learning, process technology, employee mobility, multinational firms

Knowledge has the beneficial property that it can be reused in different businesses and locations within the firm (Argote, 2013) in order to generate competitive advantage (Kogut and Zander, 1992; Grant, 1996). Reusing knowledge in this way entails the transfer of knowledge from one part of the organization to another, which in turn promotes organizational learning (Argyris and Schon, 1978; Argote and Ingram, 2000). However, firms face the difficulty that knowledge does not always transfer easily. Research has documented that the transfer of knowledge about process technologies across geographically-dispersed organizational units is time consuming and costly with varying effectiveness (Argote, Beckman, and Epple, 1990; Galbraith, 1990; Mansfield et al., 1983; Teece, 1977). Research has also shown that firms may face difficulties in transferring best practices between organizational units, including units in different locations (Szulanski, 1996, 2003). Impediments to knowledge transfer pose a challenge even for multinational firms (Gupta and Govindarajan, 2000; Jensen and Szulanski, 2004; Zander and Kogut, 1995), whose primary advantage comes from the internal transfer of intangible assets – especially knowledge – across borders (Hymer, 1960; Kogut and Zander, 1993).

To address this puzzle, in this paper we focus our attention on knowledge related to human capital (Becker, 1964) and specifically on the transfer of individuals within an organization. Transferring individuals who possess relevant knowledge from one organizational unit to another – a form of resource redeployment (Helfat and Eisenhardt, 2004; Sakhartov and Folta, 2014) – may help to overcome impediments to knowledge transfer (Argote and Ingram, 2000; Hocking, Brown, and Harzing, 2004; Kogut and Zander, 1993). Despite the potential benefits of this mechanism, which often occurs through intra-firm geographic mobility (Choudhury, 2019), a limited amount of research has examined the effect on organizational performance.

In assessing this effect, though, it is important to consider the interaction between the knowledge of individuals and organization-level factors within the units to which individuals move. In fact, research on strategic human capital has argued that there are likely to be interaction effects between factors at the individual and organizational levels of analysis (Nyberg et al., 2014). Therefore, the total effect on organizational performance of individuals and organization-level factors depends not only on their

independent effects, but also on whether the two are complements or substitutes (Crocker and Eckhardt, 2014).

Our study investigates whether intra-firm geographic mobility improves organizational performance by providing a conduit for the transfer of knowledge, and in particular whether the knowledge of individuals who move between units and factors at the organization-unit level of analysis are complements or substitutes. More specifically, we analyze the performance effects of the within-firm transfer of individuals who have expertise in innovative process technologies. Although process innovations that lower costs or raise the quality of output are important in many sectors of the economy (Tidd and Bessant, 2018), difficulties in implementing new process technologies often impede their effectiveness and raise costs in the short-term (Argote, 2013). Because transferring individuals who have prior experience using innovative process technologies also transfers their expertise with respect to these technologies, these individuals may help organizational units overcome difficulties encountered when implementing the technologies (Galbraith, 1990). For this reason, process technology usage provides an especially relevant context for understanding the role of individuals in intra-firm knowledge transfer.

Given the relatively small amount of prior research on the effect on organizational performance of intra-firm knowledge transfer through the transfer of individuals, rather than propose formal hypotheses, we ask research questions. To establish a baseline for the analysis, we first ask whether the transfer of individuals across organizational units improves performance by providing a conduit for the transfer of knowledge about innovative process technologies. Then we ask whether the innovative process technology knowledge of individuals who move between units is a complement or substitute for organization-unit level factors in the effect on the performance of organizational units.

We take these questions one step further because research on strategic human capital has suggested that whether individual human capital and organization-level factors are substitutes or complements may depend on contextual factors (Crocker and Eckhardt, 2014). In the context of process technologies, it is well established that performance is worse when organizations first introduce new technologies, due to difficulties in applying unfamiliar techniques (Argote, 2013). We therefore examine whether the answers

to the two questions posed above differ when units introduce new innovative process technologies versus when units use only innovative technologies that they have used in the past.

Our study analyzes unique proprietary data from a major multinational oil company that is well-known as a leader in the internal development and application of innovative upstream oil technologies. The frequent transfer of engineers between organizational units allows us to separate the effect on organizational performance of individual expertise from factors at the organization unit-level.

The results show that the innovative process technology-related expertise of an individual engineer who moves to a new organizational unit is positively associated with the performance of that unit, suggesting that intra-firm geographic mobility improves organizational performance by providing a conduit for the transfer of knowledge. However, the results also show that there is a substitution effect between the technology-related knowledge of engineers and organization-level factors when the unit uses only technologies with which it is already familiar, suggesting that some of the knowledge that new employees bring about these technologies is redundant. Conversely, the technology-related knowledge of engineers is a complement to organization-level factors when units introduce new technologies. Thus, individuals who bring novel expertise to their organizational units through intra-firm mobility may be important vehicles for organizational learning and building new competences, helping to diffuse best practices. These findings are consistent with a prior study showing that intra-firm geographic mobility leads to greater patenting within R&D units and may aid in knowledge transfer (Choudhury, 2016). The results in this study are also consistent with prior work suggesting that inter-firm mobility helps to diffuse knowledge (for a review, see Mawdsley and Somaya, 2016).

Beyond the literatures on knowledge transfer and employee mobility, our findings have implications for the literature on microfoundations, which has argued that individuals (or other factors) at a lower level of analysis within the organization may moderate the effects of factors at a higher level of analysis (Felin, Foss, Heimeriks, and Madsen, 2012). The evidence in this study helps to provide an improved understanding of the conditions under which such moderation is positive versus negative. This evidence is also relevant for the literature on strategic human capital that is concerned with interactions

between individuals and organization-level factors (Nyberg et al., 2014). Our findings further inform research on knowledge transfer in multinational firms (Gupta and Govindarjan, 2000; Hocking et al., 2004; Kogut and Zander, 1993) by providing evidence that the extent to which firms benefit from intra-firm mobility as a conduit for knowledge transfer depends on whether or not the expertise of individuals complements factors at the organization-unit level. Finally, this study contributes to research on resource redeployment (Folta, Helfat, and Karim, 2016) by investigating the performance effects of redeploying knowledge within the firm through the redeployment of human capital.

Background and Research Questions

Beginning with Wright's (1936) study of aircraft manufacturing, numerous studies of the introduction of new process technologies have established that costs per unit of output decline with cumulative output, often referred to as the experience curve (Argote, 2013). Research has shown that the decline in costs arises in part from organizational learning after new technologies are introduced, including through improvements in the configuration of the production process (Levitt, List, and Syverson, 2013) and on-the-job learning by workers (Thompson, 2001) (see Thompson (2012) for a comprehensive review). Firms may also seek to lower the initial high costs to organizational units of using new process technologies by transferring knowledge from other organizational units that have experience using the technologies (Galbraith, 1990).

When firms seek to transfer knowledge about process technologies, they may encounter difficulties that arise from the characteristics of the knowledge itself. In particular, causal ambiguity and lack of a proven track record for the knowledge in question may impede its transfer (Szulanski, 1996). The use of process technology tends to entail tacit knowledge (Galbraith, 1990), leading to causal ambiguity about how to use it, which in turn makes the knowledge more difficult to transfer (Szulanski, 1996). In addition, recipient units may resist the transfer of knowledge that lacks a proven track record

(Szulanski, 1996). This is likely to impede the transfer of knowledge about innovative process technologies.

Intra-firm mobility may help to overcome these barriers because the movement of experts to new organizational units and new locations also moves their knowledge (Argote and Ingram, 2000; Hocking et al., 2004; Choudhury, 2019). Individuals who have previously used innovative process technologies bring tacit knowledge about their application, which can help to reduce causal ambiguity. In addition, intra-firm mobility may improve knowledge transfer because recipients are less likely to resist an expert source (Szulanski, 1996). Experts who move across units may also help to counteract the lack of absorptive capacity on the part of recipients (Szulanski, 1996) by providing advice on the use of technological resources (Choudhury, 2019). Given the potential benefits of knowledge transfer through individuals, organizations may select individuals for their expertise when moving them to another unit. Thus, the performance effects of knowledge transfer through intra-firm mobility may come from both "selection" (of individuals who have transferable knowledge) and "treatment" (transfer of knowledge).

A limited amount of prior research has provided evidence that individuals with specialized expertise can help to transfer knowledge about technology use within an organization. In a study of stent utilization in hospitals, Greenwood, Agarwal, Agarwal, and Gopal (2019) found that physicians with specialized expertise – the skills and knowledge that individuals accumulate through learning in a particular domain (Simon, 1991) – adopted new practices more quickly and helped to diffuse these practices within the organization. In addition, Galbraith (1990) found that plants that implemented a new manufacturing technology had faster recovery of lost productivity when an engineering team from within the company that was familiar with the technology was transferred to the plants on at least a temporary basis.

In light of the foregoing research, to establish a baseline for our analysis, we ask:

RQ 1: Does the technology-related knowledge of individuals who move to another organizational unit have a positive effect on organizational performance, over and above organization-level factors?

To answer this question, we focus on individuals with expertise in innovative process technologies gained through prior experience, as part of their human capital (Becker, 1964).

Beyond the independent effect on organizational performance of the mobility of individuals with specialized expertise, the full effect depends on whether the expertise of individuals and organization-level factors are complements or substitutes (Crocker and Eckhardt, 2014; Nyberg et al., 2014). Individual expertise and organization-level factors are complements when the marginal effect on organizational performance of the combined use of individual expertise and organizational resources, including aggregate knowledge and skills at the organization-unit level, is greater than the sum of their separate effects on performance (Crocker and Eckhardt, 2014; Rothaermel and Hess, 2007). This may occur when the workflow in a unit depends on the knowledge of particular individuals (Crocker and Eckhardt, 2014). The complementarity of individual expertise and organizational resources, however, is not a foregone conclusion. If the knowledge held by an individual and an organizational unit are equifinal, the two may produce similar outcomes (Hess and Rothaermel, 2011; Rothaermel and Hess, 2007). If using one of them also marginally decreases the benefit for organizational performance of using the other, then the two are substitutes; this may occur when they are used simultaneously for the same purpose (Hess and Rothaermel, 2011).

To assess the interactive effect of individuals on organizational performance, we ask:

RQ2: Is any effect on organizational performance of the technology-related knowledge of individuals who move to another unit a complement or substitute for factors at the organizational level?

If they are complements, this magnifies any positive independent effect on organizational performance of moving individuals who have technology-related knowledge. Conversely, if they are substitutes, this detracts from any positive independent effect of moving individuals who have technology-related knowledge.

There is limited evidence regarding interaction effects on organizational performance of the knowledge of individuals and organization-level factors in the context of new technology. Based on a

measure of human capital aggregated to the firm level, research has found that the total amount of higher skilled cognitive labor within the firm and the use of information technology at the firm level are complements in their impact on firm productivity (e.g., Bresnahan, Brynjolfsson, and Hitt, 2002). At the individual level of analysis, Choudhury, Starr, and Agarwal (2020) also found in an experimental setting that the use of machine learning technology and the domain-specific expertise of individuals are complements. In contrast, Rothaermel and Hess (2007) found a negative interaction effect on firm innovative output in the global pharmaceutical industry of the number of star scientists (a proxy for expertise) and firm R&D expenditures (a proxy for R&D capability). These findings indicate that sometimes individuals' knowledge of technology and organization-level factors are complements and other times they are substitutes, but we lack a systematic understanding of the reasons for this difference.

We investigate a contingency that may shed light on the conditions under which individual expertise and organization-level factors are complements or substitutes: whether the knowledge of mobile individuals relates to technologies that are familiar or new to organizational units. The literature discussed above regarding knowledge transfer concerns knowledge and technologies that are new to organizational units. When a unit introduces new technologies, the knowledge that individuals bring about these technologies may not only contribute directly to organizational performance, but also the unit's workflow may depend more heavily on the new knowledge that resides in individuals. As a result, individual knowledge and factors at the organization-unit level may be complements. When units do not introduce new technologies and rely only on technologies with which they are already familiar, the knowledge that individuals bring with them may still contribute to organizational performance. However, in this situation some of the knowledge that individuals bring may be redundant, potentially resulting in substitution between individual knowledge and factors at the organization-unit level. Our setting and data allow us to investigate this contingency, by asking the following question:

> *RQ3: If the knowledge of mobile individuals relates to technologies that are familiar rather than new to organizational units, does this affect the complementarity versus substitution of this knowledge with organization-level factors?*

Empirical Setting

Description of OILCOMP

We explore whether the transfer of technology-related knowledge through the transfer of individuals who have expertise in innovative process technologies contributes to organizational performance in a context of substantial economic importance: the well drilling operations of one of the largest oil companies in the world. OILCOMP conducts business in all segments of the oil and gas industry. The company is a leader within the industry in the internal development and application of innovative process technologies. The firm is also highly decentralized, and is organized into units according to country of operation. These units enjoy a high degree of independence. OILCOMP became highly international many years ago at a time when poor communication technology made it difficult to direct operations in disparate countries from headquarters. Hence, the company developed a structure of country subsidiaries that adjust to local conditions.

The independence of the country subsidiaries – the organizational units in our analysis – applies to the use of innovative technology. The R&D unit at headquarters develops new technologies and can offer support for innovative technology use by disseminating information and providing advice on implementation to the country units, but headquarters cannot force the units to use innovative technologies. In addition, the country units have their own priorities, and may lead their own technology initiatives, which can overlap with similar initiatives elsewhere in the company. The firm also has a system that transfers engineers frequently between countries, which helps to transfer knowledge across organizational units. Empirically, the movement of engineers between units allows us to separate the expertise of individual engineers, gained through the use of innovative technologies in other units, from factors connected to the use of innovative technologies at the organizational level of analysis.

Well Drilling and Innovative Technology

Oil companies first conduct exploration activities to try to discover new sources of oil, the companies then conduct development activities to prepare fields for production, and finally the companies start production (Stadler, 2011; Stadler, Helfat, Verona, 2013). In the first phase, companies drill exploration wells based on seismological studies that provide a preliminary understanding of the local subsurface geology. If the companies discover oil and gas, they undertake further analysis to decide how and where to drill development wells. Well drilling is a highly complex process that consists of distinct activities. For example, during drilling, the wellbore pressure must be monitored, the equipment must be lifted, the borehole must be cased and cemented, and a drill-bit must be deployed. When oil companies intend to drill, they must decide which technology to use for each activity in the drilling process, such as which drill bit and casing to use and how to monitor pressure during drilling operations.

For each activity in the drilling process, firms can choose either an established or an innovative technology. Each innovative technology applies to only one activity in the drilling process and each innovative technology covers a different activity in the process, so in theory a firm could use all of the innovative technologies when drilling a well. None of the innovative technologies is superior to the others because each technology applies to a different activity in the drilling process, and no activity dominates the others in importance. In addition, each activity is potentially a bottleneck in the drilling process because failure to complete all of the activities will make it impossible to finish drilling the well. Moreover, due to the complexity of geologic formations, firms cannot always tell which technologies are likely to work best until they start drilling. Thus, no specific technology is more important than another, and it is the number of innovative technologies that are used which affects drilling performance.

In general, firms use an innovative technology for more difficult drilling conditions when they expect that an established technology will not perform as well. The use of an innovative technology reduces the amount of time that it takes to drill a well, so firms do not need to pay for personnel, equipment, and materials for as long a time period, which reduces costs. However, an innovative technology is also more expensive to deploy than an established technology due to higher material and equipment costs. This means that in deciding whether to utilize an innovative technology, firms must balance cost savings from a shorter

drilling time against the higher cost of the technology. The decision is not straightforward due to the difficulty of ascertaining which technologies will work best. In addition, firms that are unfamiliar with an innovative technology may be uncertain about how well it will perform. Firms therefore may hesitate to use an innovative technology if they are not sure whether improved performance will offset the additional expense. Moreover, if firms have never used a particular innovative technology before, they may have to bear additional costs such as the costs of initial missteps in applying the technology, as suggested by the experience curve literature on the introduction of new process technologies discussed earlier.

If a firm decides to use an innovative technology, it is generally because on balance the firm expects an innovative technology to reduce well drilling costs. As noted above, firms can use more than one innovative technology per well and all technologies are equally important. It follows that the greater is the number of innovative technologies used to drill a well, the greater is the effect on well drilling performance.

Innovative Technologies in OILCOMP

To better understand the role of individuals and organizational units in technology usage in OILCOMP, we interviewed 22 engineers involved in the adoption of three types of innovative technologies [Swellables, Managed Pressure Drilling (MPD), and Soft Torque Rotary System (STRS)] as well as other innovative technologies. Despite the potential cost advantages of using innovative technologies, not all units are equally familiar with these technologies. In addition, our interviews indicated that country units are often skeptical that more costly innovative technologies will improve performance, and managers and well engineers may be reluctant to introduce an additional element of risk into operations already characterized by uncertainty. For example, one senior well engineer commented that: "…our operating arms…don't…even want new technology unless it's absolutely proven beneficial."

Our conversations also indicated that country units have distinct, locally-composed strategies with respect to technology use, and there is heterogeneity in how welcoming the units are to new technology. Path dependency, the track record of old technology, and unit size appear to be at play here. For example, the first operational applications of STRS took place in a unit that had been a pioneer in the original (predecessor) Soft Torque technology and strongly believed in its potential. Units were also more open to

trying a new technology when more established technology simply did not deliver. For example, a deep-water project drilled nine unsuccessful sidetracks (secondary wellbores away from the original wellbore) using conventional approaches, before it was prepared to try MPD, a more innovative technology that turned out to be suitable. In addition, our informants mentioned that units which drill a large number of wells have a greater ability to experiment with new technologies in several wells without harming the overall performance of the unit.

Within OILCOMP, the decision of which technologies to use is reached by consensus within an organizational unit, involving the set of engineers working in an oil field where drilling takes place together with the business manager responsible for oil field operations and the head of technology for the unit. The set of engineers is also responsible for implementing the deployment of technologies in the oil field in consultation with the business manager and the head of technology for the unit. Thus, technology usage within a unit is an organization unit-level phenomenon.[1]

The expertise of an individual engineer can also have an additional effect on well drilling performance. Our informants indicated that an individual engineer's expertise may be especially important during the deployment of an innovative technology after it has been chosen for use by the unit. Implementation of innovative technologies in well drilling depends substantially on tacit knowledge, and the expertise of individual engineers who have had prior experience with the technology can be helpful. One example involves Swellables, a technology where plastic components expand when they are in contact with water, shutting out sections of the well where water rather than oil enters the wellbore. In this instance, a well that was drilled "barefoot" (without a casing or liner) provided ideal conditions to try using the technology. The prior experience of an individual engineer turned out to be invaluable in deploying the technology effectively, and the well became highly productive at a lower cost than would have been possible using established technology.

Internal Mobility of Engineers

[1] Individual engineers move in and out of organizational units frequently and operational needs differ over time depending on the number and types of wells to be drilled, so units do not have dedicated teams.

OILCOMP has a sophisticated human resource management system, and runs an internal labor market for engineers: country units post job openings and engineers seeking to transfer between country units apply for jobs. Engineers are expected to move frequently between units in order to advance in their careers. Where engineers move and when depends on a variety of factors. National regulations affect which units are seeking to hire engineers, as some governments impose quotas on how many foreign specialists the units can employ. The attractiveness of a location in terms of quality of life also matters to engineers, and OILCOMP takes this into consideration by offering higher pay in unattractive locations. Engineers may also consider the chances of future promotion in their job choices, as some locations – often larger country units - are of strategic importance to the company and therefore receive more attention from top management. Finally, personal fit and qualifications for a particular job matter. This might include expertise on innovative technologies, although in our interviews this was not mentioned as a factor. Nevertheless, in the empirical analysis, we account for the possibility that the assignment of engineers to organizational units based on innovative technology experience could affect well drilling performance.

Applying the Research Questions in this Study to OILCOMP

The data from OILCOMP make it possible to investigate the extent to which the expertise of individual engineers with respect to innovative technologies contributes to organizational performance, over and above the impact of organization-level factors connected with innovative technology usage. We further investigate whether there is an interactive effect between the technology-related knowledge of individuals and organizational usage of innovative technology, and if so, whether the two are complements or substitutes. Given OILCOMP's decentralized structure, organizational performance and organization-level factors are measured at the level of the organizational unit. To assess the impact on organizational performance, we use a standard measure of performance in the industry, well drilling costs per meter.

As noted earlier, firms in the upstream oil industry use innovative technologies in an effort to lower costs, and no one innovative technology is more important than another. Instead, it is the number of innovative technologies used by an organizational unit that affects how much costs are reduced (all else equal, such as the number of wells drilled). The technology-related expertise of an individual engineer may

have an additional effect on the well drilling performance of an organizational unit. Substantial research has documented that greater prior experience of individuals in a particular domain results in greater individual expertise (see Greenwood et al., 2019). Therefore, we measure the expertise of individual engineers with respect to innovative technology usage as their prior experience using innovative technologies. Given that units cannot tell ahead of time which technologies will prove most useful and given that no technologies are more important than others, an engineer has greater potential to improve the drilling capabilities of the unit – and thereby decrease costs – when he or she has expertise in a larger number of innovative technologies. To assess whether individual-level expertise and organization-level factors are complements or substitutes (or neither) with respect to their effect on organizational performance, we interact individual-level innovative technology expertise with organization-unit-level innovative technology usage.

As discussed earlier, performance is generally worse when organizations first introduce new process technologies, due to difficulties in applying unfamiliar techniques (Argote, 2013). Thus, it is not surprising that units in OILCOMP are often reluctant to try new technologies due to uncertainty about how well the technologies will work. The decentralized structure of OILCOMP exacerbates this uncertainty, because knowledge does not transfer easily between units. Therefore, when units try new technologies, they may incur costs due to missteps in applying the technologies. This in turn may affect the impact on performance of innovative technology use by a unit. If the costs associated with new technology introduction are high enough, well drilling costs could even increase rather than decrease. In addition, research shows that new technologies may require individuals to perform different tasks when implementing the technology (Choudhury, Starr, and Agarwal, 2020), which suggests that the expertise of individual engineers during the deployment of new technologies may affect performance. We therefore investigate whether the effects on performance of the number of innovative technologies used by a unit, the innovative technology-related expertise of an individual engineer, and the interaction between them differs when units introduce innovative technologies that they have not used previously versus using innovative technologies that the units have used in the past.

In bringing our data to bear on these questions, we control for a large number of additional factors that are likely to affect well drilling costs per meter at the level of both the organizational unit and the individual engineer. These factors include other types of drilling-related expertise of individual engineers, the overall ability of each engineer, the technology-related expertise of other engineers in each organizational unit, characteristics of each unit that might affect well drilling performance, and unit fixed effects (to control for more versus less able units overall), which otherwise might provide alternative explanations of our findings. We do not control for engineer fixed effects. The transfer of knowledge across units through the movement of engineers does not depend on or require changes in the expertise of individual engineers over time. In addition, controlling for engineer fixed effects would make it impossible to ascertain the effect of the time-invariant portion of an engineer's expertise on the performance of the unit to which the engineer has moved, which would be problematic given that engineers' expertise changes slowly over time.

As noted earlier, the effects of moving individuals with specialized expertise may reflect both selection (the hiring of individuals with innovative technology expertise) and treatment (the application of individuals' expertise within their units). In our main analysis, we investigate the treatment effect insofar as possible within the limits our data using instrumental variables. Then, in a robustness analysis, we investigate whether accounting for selection effects using a Heckman type of analysis that allows for endogenous regressors with fixed effects alters the results of our main analysis. We next explain our data, variables, and empirical methods.

Data, Variables, and Methods

Data

Our analysis draws on three different types of data to create a nine-year longitudinal dataset covering the years 2004 to 2012. The first set of data on OILCOMP'S well drilling and innovative technology usage covers all wells drilled (7135 wells) between 2000 and 2012. None of the innovative

technologies, which were relatively new to the industry, was used by OILCOMP prior to 2000. We merged these data with a second dataset that contains information on all previous job assignments for every engineer employed by OILCOMP in 2015. For each job assignment of an engineer, the data include the location (country unit), the start and end date of the assignment, the individual's engineering specialization, age, nationality, level of seniority, the date when the individual first joined the company, as well as the company's assessment of the individual's potential for future promotions. The data cover 33,642 assignments, with the earliest one starting in 1979. Finally, we obtained data on oil prices from the U.S. Energy Information Agency (EIA).

We applied several criteria in merging these data to create our dataset. First, we included only job assignments from the 22 country units where drilling operations take place. Second, we included only job assignments during the time period for which we also have well drilling and technology usage data. Third, because OILCOMP's data on engineers are organized by job assignment, we organized the merged dataset according to the job assignment of an individual engineer. We matched each job assignment with data on well drilling and innovative technology usage in an engineer's organizational unit during the time period of an assignment, as well as oil price data.[2] Fourth, to measure an engineer's prior experience with innovative technologies and well drilling conditions, we used data from the engineer's previous job assignments within the company. Prior to an engineer's first (earliest) job assignment in the merged panel, we have no information about his or her previous exposure to innovative technologies. As a result, it is not possible to measure an engineer's prior experience with innovative technologies for the engineer's first job assignment in the dataset. Therefore, we dropped observations for the first (earliest) job assignment for each engineer, although data from the first job assignment are used to construct engineer-specific explanatory and control variables for subsequent job assignments.

[2] As noted above, OILCOMP's engineer-level data are structured according to individual assignments. To capture the prior exposure of individual engineers to well drilling environments and innovative technologies, we included wells that were in progress in the country of assignment during the period of each individual assignment. This included wells for which drilling started prior to the engineer's arrival but finished either during the assignment or extended beyond it, as well as wells for which drilling started during the engineer's assignment.

Applying these criteria reduced our final sample to 3,208 observations, covering the years 2004 to 2012. Each observation is a job assignment of a single engineer in a single organizational (country) unit. The sample includes 633 individuals who on average have 5 assignments, with a standard deviation of 3.8, and a minimum of 1 and a maximum 20 assignments. Forty-five percent of the engineers have a managerial role, largely as supervisors of well drilling projects (30 percent of all engineers), but 15 percent of the engineers are in a more senior role. The mean length of an assignment is 198 days.

Despite the richness of our dataset, we note three limitations. First, our dataset includes only engineers working for OILCOMP in 2015. This raises the question of whether there are systematic differences between engineers who were hired more recently and those who had worked for the company throughout the sample period. An examination of the data shows that the mean values for the number of days spent on an assignment, tenure in OILCOMP, seniority level, and the company's assessment of an engineer's future potential are similar in the first and last year of our merged dataset. This suggests that there are not systematic differences over time in the sample of engineers on these dimensions.

Secondly, the first year in the panel dataset is 2004 and data on individual engineers' technology usage in prior assignments begins in the year 2000. Because job assignments in later years allow for more experience accumulation subsequent to the year 2000, we control for the last year of each assignment and for the number of days of each assignment, which in combination control for the first year of each assignment. In addition, an engineer is likely to have been exposed to a larger number of innovative technologies the longer that he or she has worked for the company, all else equal. For this reason, we control for the total length of time that an engineer had worked for OILCOMP prior to each assignment. Engineers that had previously worked for other companies may also have been exposed to innovative technologies. Therefore, we control for whether an engineer had worked outside of OILCOMP during his or her career.

Finally, the structure of the well, technology, and individual career data reflects technology data on the country unit level. In OILCOMP's decentralized system, country units have responsibility for operational decisions, including which technologies to deploy. Although units make drilling decisions for

each oil field separately, unfortunately data are not available that would make it possible to conduct sensitivity analyses at the project (oil field) or well level.

Variables

We define our variables at the job assignment level – that is, during the time period of an assignment of an engineer to an organizational unit – because this is how the OILCOMP personnel data are structured. Therefore, we measure the performance of an organizational unit during each job assignment.[3] Other variables are also measured at the job assignment level.

Dependent Variable

We use the standard measure of well drilling performance in the industry, drilling cost per meter. Because this measure is highly skewed, we log transformed it: $Log\ (\frac{Total\ costs\ of\ all\ wells\ drilled}{Total\ number\ of\ meters\ drilled})$. The total costs of all wells drilled in a unit during an assignment includes all costs of operations.[4] The total number of meters drilled is the combined depth in meters of all wells drilled during an assignment.

Independent Variables

Unit innovative technology use: The categorization of innovative technologies comes from OILCOMP, which uses a common classification in the industry developed by Rushmore Reviews, a large provider of data services to the upstream oil industry. There are 11 innovative technologies: low rheology mud, pressure managed drilling (MPD), onshore operation centers for control of drilling processes, slimhole, intelligent drill pipe, expandable casing, bi-centred bit, lightweight cement, dual derrick, pressure monitoring while drilling, and other. OILCOMP did not use intelligent drill pipe technology in the drilling operations in our sample. Given that we are interested in how many different innovative technologies a unit uses (controlling for the number of wells drilled), we count the number of innovative technologies used at

[3] Although we lack data at the oil field or well level, an engineer may work on more than one well or oil field in a unit during an assignment. Nevertheless, measuring performance at the unit level rather than the oil field or well level makes it more difficult to pick up an effect on performance of the expertise of an individual engineer.

[4] These include the cost of general overhead, base operations, staff overhead, incentive payments, well logging, transportation, materials, materials supply, marine vessel support, marine supply base, port facility, warehousing, well design and programming, site survey, well preparation and reinstatement, oil rig mobilization and demobilization, well completion, and well test operations.

least once by the unit during an engineer's job assignment.[5] The maximum number of technologies used by a unit at least once during a job assignment was seven.

Engineer innovative technology experience: This variable is a count of the number of different innovative technologies used at least once during any of an engineer's prior assignments. The variable is calculated similarly to the unit innovative technology use variable except that the number of technologies is based on the past assignments of an individual engineer. Although individual engineers may not have worked on every well drilled in their units during prior assignments, our interviews indicated that engineers exchange information frequently within the units and engineers are exposed to the different well drilling technologies used in their units.

Control Variables

Co-worker high level of innovative technology experience: In order to tease out the impact of individual experience with innovative technologies, we need to control for the prior experience of co-workers within the unit. We first calculated the total number of innovative technologies that each co-worker (i.e., another engineer working in the same unit as the focal engineer during the time of the focal engineer's assignment) had experience with in prior assignments, and summed these for all co-workers. Because this measure is highly correlated with *engineer innovative technology experience*, we created a binary (0,1) variable indicating whether the amount of co-worker experience was in the top quartile. Hence, this variable captures whether co-workers had substantial prior experience with innovative technology.[6]

We also control for several engineer-specific characteristics that could affect well drilling performance, including measures of experience other than experience with innovative technologies.[7] *Experience in headquarters (HQ) location* is a binary variable indicating whether an engineer had prior

[5] As explained earlier, it is the number of innovative technologies that are used that determines well drilling outcomes. We do not use an alternate variable that counts the total number of times that innovative technologies were used because this does not measure the number of technologies that were used. In addition, the total number of innovative technologies that were used is highly correlated with the size of each unit, which introduces the potential for multicollinearity to affect the coefficient estimates.

[6] Using the total number of innovative technologies that co-workers had experience with does not change the results for the explanatory variables and their interaction, but this co-worker experience variable has an implausible negative relationship with unit performance. This is likely due to multicollinearity, which can cause the signs of coefficient estimates to switch.

[7] The control variables do not include education as is common in the human capital literature, because virtually all of the engineers in our sample have the same type of engineering degree and there is little variance in the level of education.

experience in a headquarters location. Because OILCOMP's main technology development center as well as several initiatives that support technology are located at its headquarters, we would expect that prior headquarters experience would increase the chances that an engineer had been exposed to innovative technologies. At the same time, our interviews also suggested that units might resist headquarters-driven technology initiatives. Country units might therefore receive engineers with headquarters experience with some reluctance, making them less effective.

OILCOMP specifies which skills (unconnected to innovative technologies) are needed for a particular job. For drilling operations, there are four relevant *job skill specifications*: *well engineering, completion and integration, other engineering,* and *commercial.*[8] For each job assignment, we created binary variables for each of the last three to indicate whether the skill was a requirement for the assignment, and therefore whether the engineer would have possessed the skill at the start of the assignment. The job skill specification of well engineering is the omitted dummy variable.

We control for two types of engineer experience with different geological and geophysical conditions. *Offshore and onshore experience* is a binary variable that indicates whether an engineer had prior experience with both offshore and onshore operations versus only one type. *Experience in different reserve types* is a count variable that captures how many different types of reserves an engineer has previously worked with. OILCOMP identifies five different reserve types, namely, conventional, shale, high pressure, high temperature, and salt formations.

The amount of time that an individual has spent working as an engineer can contribute to the engineer's general ability. We therefore control for the firm-specific experience of each engineer, using the

[8] *Other engineering* includes Civil & Structural Engineering, Electrical Engineering, Engineering Management, Engineering Materials and Corrosion, Engineering Mechanical – Static, Engineering Mining, Engineering Offshore Structures, Engineering Pipelines, Engineering Production Automation, Control & Operations, Quality Engineering, Subsea, Maintenance Downstream, Maintenance Upstream, Operational HSSE, Petroleum Engineering, Petrophysics, Reservoir Engineering, Process Engineering Exploration & Production, Process Engineering Oil & Gas Production Systems, Process Engineering Production Control & Optimization, Process Safety, Production & Manufacturing Management, Production & Manufacturing Operations, Production & Manufacturing Product Quality Control, Production Operations Upstream, Production Technology & Production Chemistry, Project Engineering, Project Services. *Commercial* includes Asset Management, Business Administration and Support, Business Information and Data, Commercial Business to Business (B2B), Commercial Upstream, Contracting and Procurement, Corporate Affairs, Finance Controlling and Accounting, Finance Internal Audit, Gas Commercialisation, General Management Country, General Management Global, General Management Zonal, Real Estate, Business Analysis, Management & PE, Economics & Scheduling.

variable *total time in firm*. This variable is a count of the number of days since an engineer first joined OILCOMP, as of the start of each job assignment. Because this variable is skewed, we log transformed it. More experience in OILCOMP might enable engineers to make more appropriate decisions with regard to drilling operations. As noted earlier, this variable further controls for experience with innovative technologies within OILCOMP prior to the start of an assignment. It is also possible that longer tenure in the firm might lead to inertia and a reluctance to change course. Longer tenured engineers may also be paid more, raising costs. In addition, we constructed a binary variable, *prior experience outside of firm*, that captures whether an engineer had prior experience outside of OILCOMP. This variable controls for the possibility that an engineer might have had more experience than the *total time in firm* variable captures.

To further control for the general ability of the engineer, we use two variables. OILCOMP's HR system identifies the current level of seniority (i.e., rank) within the company for each engineer and the potential level of seniority that the engineer is forecast to eventually attain. OILCOMP typically identifies the *seniority potential* of each employee soon after the person begins work at the company, which is an assessment of the ability of the employee, and revises it over time as the company gains more information about the employee. To some extent, the seniority potential of an engineer creates a self-fulfilling prophecy, because more attractive jobs may be easier to get for those viewed as having higher potential. This variable has a value of 1 for individuals with the potential to reach seniority level 1, a value of 2 for individuals with the potential to reach seniority levels 2 or 3, a value of 3 for individuals with the potential to reach seniority levels 4 and 5, and a value of 4 for individuals who might reach seniority levels 6, 7, or 8. *Seniority level* indicates the current level of seniority (rank), the value of which varies from 1 to 14, with 1 being the most senior and 14 the least senior. Drilling operations do not involve top executives and the most senior engineers in our sample are classified as 4. Only 1.34% of the observations in our sample fall into this category.

We control for assignment-specific factors at the level of the individual as well. The length of an assignment might affect an engineer's impact on performance, so we control for the number of *days on assignment*. A longer assignment permits an engineer to develop a more intimate knowledge of a unit and

the local geology. At the same time, we know from our interviews that OILCOMP sees the transfer of engineers as a substantial part of their development. It is possible that less successful engineers find it harder to get new job offers and therefore stay in each assignment longer.

In addition to control variables specific to individual engineers and their co-workers, we control for characteristics of the unit that might affect well drilling performance. First, we include controls for the scale of operations. The *number of wells drilled* captures the number of opportunities that a unit has to experiment with new technologies. If a unit drills many wells and an innovative technology is used in one of them but it does not perform as expected, this has less impact on the unit's overall performance than in a smaller unit. In addition, a larger number of wells may have the advantage of economies of scale. Because the number of wells does not fully capture the scale of operations, due to differences in costs of individual wells, we also control for *total well cost*, the total amount spent on drilling in a unit during an engineer's assignment. We log transformed both variables as they are highly skewed.

We also control for whether the unit used a *top international drilling contractor.* Most firms use drilling contractors to supplement their operating capabilities. For example, in OILCOMP, it may not be cost effective for smaller units to maintain their rigs in-house. However, at OILCOMP drilling contractors are not involved in the choice of which technologies to use. The largest and best-known contractors may be more skilled at conducting drilling operations, potentially reducing well drilling costs, but their services may also be more expensive because these contractors are in a stronger bargaining position due to their size and expertise. We first created a binary variable for each well that indicated whether one of the world's 10 largest drilling contractors was used. Then we added up the binary variables for all wells drilled during an assignment, creating a count variable.

Exploration well is a count of the number of exploration wells drilled during an assignment. Exploration wells, which are drilled in search of new oil, are generally more challenging and costly to drill because the firm cannot rely on prior knowledge of the geology. At the same time, firms might plan more carefully because they are aware of the challenges. Similarly, *offshore rig* is a count of the number of wells

drilled offshore. These wells are typically more difficult and costly to drill than onshore wells but again, firms might plan more carefully when drilling these types of wells.

Oil firms measure the number of *total non-productive days* when they halt drilling operations for an oil field, due to difficulties encountered during drilling or for economic reasons unrelated to drilling performance. For example, it may turn out that a different oil field holds more immediate promise in terms of reserves or a firm may decide to wait for a more favorable oil price before it continues to drill. A larger number of non-productive days (across all oil fields in a unit) affects both the number of meters drilled and total well drilling costs, because no drilling costs are incurred and no meters are drilled during a halt to drilling for an oil field.

Finally, we include unit-level (country) fixed effects to account for time-invariant factors specific to each unit that might affect drilling costs but are not accounted for by the other control variables, such as the time-invariant overall drilling capability of the unit. We also include *oil price* in the first year of each assignment, measured as the year-end U.S. refiner acquisition cost of crude oil.[9] When the price of crude oil is high, firms will make more resources available for drilling. We expect the impact on drilling efficiency to be negative. Because higher oil prices make it possible to make profits while drilling more costly wells, firms are likely to drill more wells in more difficult operational environments. We further included a dummy variable for the *last year of an assignment* in order to control for temporal effects other than oil prices, including the effect mentioned earlier that assignments in later years would allow more time for engineers to accumulate experience with innovative technologies.

Methods

In our base regressions, we use OLS estimation with unit (country) fixed effects. We first estimate the model without the interaction between unit innovative technology use and engineer innovative technology experience, and then we include the interaction term. In addition, we estimate two stage least squares (2SLS) instrumental variables regressions with unit fixed effects to account for potential

[9] Refiner acquisition cost reflects how much a firm can earn from selling a barrel of crude oil to refiners in the U.S., and is a composite price for imported and domestic oil.

endogeneity associated with the explanatory variables. Although we control for many unit-level and engineer-level factors, there may still be omitted variables that are correlated with our variables of interest. In addition, there may be reverse causality from well drilling performance to innovative technology use, particularly if high costs lead a unit to use a larger number of innovative technologies in an effort to reduce costs. Thus, both of the explanatory variables could be subject to endogeneity, as might the interaction of these variables. Later in the analysis we also investigate the possibility of sample selection bias if an organizational unit takes innovative technology into account when hiring engineers.

In the instrumental variables model without the interaction term, we use four instruments for the potentially endogenous variables of unit innovative technology use and engineer innovative technology experience. In the instrumental variables model with the interaction term, we include an additional instrument for the interaction term. These instrumental variables are likely to be correlated with the variables that measure a unit's innovative technology use or the innovative technology expertise of an individual engineer, but are unlikely to have a direct effect on well drilling performance during the time period when drilling occurs, as explained below. As reported later, the Hansen J test of overidentifying restrictions provides support for this logic.

The first instrument is the number of times that a unit used innovative technologies in the year immediately prior to the start of a job assignment in the unit. The frequency of innovative technology use in the year prior to the start of an assignment should not directly affect well drilling costs during an assignment because different wells are usually involved. How often a unit uses innovative technologies, and the number of innovative technologies that a unit uses, change substantially from one year to the next depending on the wells being drilled at the time.[10] However, the frequency of innovative technology usage in the prior year may be correlated with the current number of innovative technologies used by each unit if units that used innovative technologies more frequently in the recent past are prone to use a larger number of innovative technologies in the near future.

[10] Because this instrument reflects technology use in only one year, and technology use varies from year to year within a unit, the instrument does not capture the accumulated experience of a unit using innovative technologies.

The second instrument is a binary variable for whether an engineer had experience drilling complex wells in prior assignments. Complex wells are those for which drilling is not strictly vertical. Different complex wells use different combinations of technologies due to differences in the unique geological formations in which the wells are drilled. The uniqueness of geological formations involved in complex wells means that experience with complex wells does not transfer well between assignments, so an engineer's prior experience drilling complex wells is unlikely to directly affect current well drilling costs. However, innovative technologies are more likely to be used in drilling complex wells. Therefore, prior experience with complex wells might be correlated with an engineer's prior experience with innovative technologies, and might affect costs indirectly through the engineer's innovative technology expertise.

A third instrument captures the extent to which an engineer held managerial positions prior to the current assignment. It is a count of the total number of the engineer's prior assignments that had a managerial job title above the level of supervisor, which is a low-level managerial position. Greater prior managerial responsibility might have provided greater exposure to innovative technologies, and therefore may be correlated with an individual engineer's innovative technology experience and expertise. Prior managerial responsibility might also affect whether an individual currently holds a managerial position, but we control for a current managerial position through the seniority level variable. Beyond these factors, it is unlikely that prior managerial experience would directly affect current well drilling costs independent of other types of well drilling experience that are already included in the model.[11]

The fourth instrument is a count of the number of times that an engineer had previously used the innovative technology with which he or she had the most prior experience, a measure of the engineer's innovative technology specialization. This is likely to be correlated with the number of innovative technologies in which an engineer has expertise, since both variables will tend to increase as an engineer's prior well drilling experience increases. However, because no one technology is more important than another and because the technology in which an engineer has the most expertise is no more likely to be

[11] Although it might seem that prior managerial experience could sensitize an engineer to the need to control costs, this is unlikely because most of the managerial positions in our data do not involve direct budgetary responsibility.

used than any other technology, the depth of an engineer's prior experience with a specific technology would not have a systematic effect on current well drilling costs. Finally, in the model that includes the interaction term between the two explanatory variables, we include a fifth instrument consisting of the interaction between prior unit innovative technology usage and engineer managerial experience. The models are estimated using *xtreg* (OLS fixed effects) and *xtivreg2* (2SLS fixed effects) in Stata 16.

Results

Table 1 reports descriptive statistics, and Table 2 reports correlation coefficients for the full sample. It is notable that units used relatively few innovative technologies per assignment; the average value is 1.50, with a minimum of zero and a maximum of seven. The mean value of engineer innovative technology experience is considerably higher, with a mean value of 3.52, a minimum of zero and a maximum of 10. Table 3 reports the results for the OLS and instrumental variables models. In Table 3, models 1 and 2 report results for the OLS regressions estimated with robust standard errors clustered at the unit level.[12] Models 3 and 4 in Table 3 report results for the 2SLS instrumental variables regressions with robust standard errors. A Hausman type test confirms that the three variables are endogenous.[13]

In what follows, we focus on the 2SLS instrumental variables results, because the OLS results are subject to endogeneity. We also concentrate on the results that include the interaction term in model 4, given our primary interest in understanding whether individual and organization level effects are complements or substitutes. The estimated coefficient on the interaction term between the two explanatory variables is statistically significant, indicating that the level of one variable moderates the strength of the relationship of the other variable with respect to performance. In model 4, a test for under-identification rejects under-identification (Kleibergen-Papp rk LM statistic value of 49.667, p-value=0.000). A test for weak identification using the Cragg-Donald Wald F statistic and the Stock-Yogo critical values rejects the

[12] The table does not report a constant term for the instrumental variable models 3 and 4 because the *xtivreg2* routine does not estimate a constant term for models with fixed effects (see https://www.stata.com/statalist/archive/2012-07/msg00078.html).
[13] It is not possible to estimate cluster robust standard errors using 2SLS due to the structure of the data, because some units have a small number of observations. The Hausman type test was performed using the *endog* option in the *xtivreg2* routine in Stata.

hypothesis of weak identification based on 5% maximal relative bias at the 5% level of significance (the threshold for no more than 5% maximal bias is 9.53, which is exceeded by the value of 10.32 for the Cragg-Donald Wald F statistic). A test for over-identification fails to reject the null hypothesis that the over-identifying restrictions are valid (Hansen J statistic value of 1.55, p=0.461).[14] Thus, the test fails to reject the hypothesis that the instruments are independent of the errors in the second-stage performance regression.

Several of the control variables in model 4 are statistically significant. The estimated coefficients for the variables for the scale of well drilling – the total number of wells drilled and total costs of well drilling – have large magnitudes in addition to high statistical significance. Drilling a larger number of wells is associated with lower costs per well, suggestive of economies of scale. In addition, higher total drilling costs are associated with higher costs per well. Other statistically significant drilling-related variables include the use of a top drilling contractor, which is associated with higher costs, consistent with the ability of these contractors to command higher prices for their services. Additional statistically significant drilling-related variables include the number of wells drilled offshore, which is positively associated with costs per meter, and the number of non-productive days, which is negatively associated with costs, as expected. Some control variables at the level of the individual engineer are also significant. Prior experience with different types of reserves is associated with lower costs per meter, as is co-worker innovative technology experience. *Seniority level* (which is reverse coded such that more junior engineers have a higher value of the variable) is also associated with lower costs. It is possible that all else equal more junior engineers have a larger impact on drilling costs because they are more directly involved in drilling operations and therefore make important implementation decisions. Having both onshore and offshore experience as well as length of time employed by the company are associated with higher costs per meter. The estimated coefficient for onshore and offshore experience may reflect that individuals with broader experience are paid more and are

[14] Model 3 passes the underidentification test (Kleibergen-Papp rk LM statistic value of 173.436, p=0.000), the weak identification test (based on Cragg-Donald Wald statistic of 51.492, which exceeds the Stock-Yogo critical value of 11.04 for 5% maximal bias and p<0.05), and the overidentification test (Hansen J statistic value of 3.276, p=0.1943).

therefore more costly. The positive coefficient estimate for length of time employed by the company may reflect less up-to-date skills or higher pay for longer-tenured employees. In addition, experience in the headquarters location and the number of days on an assignment are associated with higher costs.

For the explanatory variables, both innovative technology use by the unit and innovative technology experience of an individual engineer are statistically significant, and are associated with lower costs per meter before accounting for the interaction effect. The estimated coefficient on unit innovative technology use indicates that the use of one additional innovative technology is associated with a 15.4% reduction in costs per meter (exp(0.1435)=1.154). At an average total drilling cost of approximately 290 million dollars for a unit during an assignment, a 15.4% reduction in costs amounts to an average of 44.7 million dollars. The estimated coefficient on engineer innovative technology experience indicates that an engineer's experience with one additional innovative technology is associated with a 4.2% decrease in costs per meter (exp(0.0413)=1.042), or $12.2 million dollars on average per engineer during an assignment. Given that an engineer has an average of five assignments in our sample, the total costs savings per engineer for additional innovative technology experience are substantial.

The interaction between these two variables is also statistically significant, but the coefficient is positive, indicating that the interaction is negatively associated with performance (costs per meter are higher). Figure 1 displays the estimated interaction effect graphically. The results indicate that individual engineer innovative technology expertise and unit innovative technology use are substitutes: a higher level of individual engineer experience with innovative technology reduces the strength of the relationship between unit innovative technology use and lower costs, and vice versa.

Robustness Analysis for the Full Sample

The analysis thus far provides evidence that the innovative technology expertise of an individual engineer has an effect on well drilling costs over and above factors at the organizational level of analysis. However, an organizational unit often has more than one engineer working on a well and the impact of an individual engineer may vary depending on the number of engineers who are working on a well. The number of engineers per well tends to vary depending on drilling conditions, and there are generally fewer

engineers per well for wells that are easier to drill. Thus, having fewer engineers per well does not mean that an engineer would necessarily have a larger effect on well drilling costs. However, to assess whether the results thus far hold up when there are fewer engineers per well, we conducted a separate analysis of assignments for which the average number of engineers per well during an assignment was below the mean of 7.3. Table 3 reports the results of this subsample analysis in models 5 (OLS) and 6 (2SLS), which include the interaction term.[15] The results are consistent with those in the full sample.

The results in the full sample could also be subject to sample selection bias if organizational units take innovative technology into account when hiring engineers. Although important considerations in hiring an engineer are likely to include factors such as whether the engineer meets the *job skill specification* for the position, expertise in innovative technologies could also affect the hiring decision. For example, because a unit cannot predict prior to drilling which innovative technologies will be most useful, the unit may prefer greater breadth of expertise among its engineers. Therefore, when making a hiring decision, a unit might take into account the number of innovative technologies in which its engineers currently have expertise. A unit that has expertise in fewer innovative technologies among its engineers might seek to hire engineers who have greater breadth of experience.

We conduct a formal test for selection bias in the presence of endogenous regressors using the procedure developed by Semykina and Wooldridge (2010) for panel data with fixed effects. As explained in the online supplement, the analysis entails estimating a first stage probit selection model that controls for fixed effects, and then estimating a second stage 2SLS model with fixed effects that tests for sample selection bias. The dependent variable in the probit model is a binary variable indicating, for each engineer employed by the company in each year, whether the engineer was hired into a unit during that year or stayed in their current position. As an instrument in the probit model, we use the innovative technology expertise of the engineers in a unit in the year prior to hiring, *prior year engineer innovative technology experience*

[15] Model 6 passes the underidentification test (Kleibergen-Papp rk LM statistic value of 73.059, p=0.000), the weak identification test (based on Cragg-Donald Wald statistic of 17.649, which exceeds the Stock-Yogo critical value of 9.53 for 5% maximal bias and p<0.05), and the overidentification test (Hansen J statistic value of 2.58, p=0.2752).

per unit. The instrumental variable is constructed as the count of the number of different innovative technologies used in the past by all engineers working in a unit in the prior year. The 2SLS coefficient estimates for our explanatory variables reported in the online supplement are very similar to those reported earlier, and there is no evidence of sample selection bias.

The robustness analyses support the original results that the interaction of individual expertise and organization-level factors has a negative effect on organizational performance, and that the two are substitutes. Next we examine whether the results depend on whether units introduce new technologies.

Comparison of Assignments With and Without the Introduction of New Technology

The organizational units in our sample differ in whether they use only innovative technologies that they have used in the past and are therefore already familiar with, or whether they also use innovative technologies with which they are unfamiliar. In 48% of the assignments, units introduced at least one new innovative technology that they had not used before. When units introduce new technologies, organizational units and individual engineers may have difficulty implementing innovative technologies with which they are unfamiliar, and this may affect the main effects of these two factors as well as the interaction effect.

To investigate the impact of new technology introduction, we split the sample into two subsamples: 1) assignments during which the units adopted at least one new innovative technology, and 2) assignments during which the units adopted no new innovative technologies. In our setting, when units introduced new technologies, they tended to use more innovative technologies in total. The mean value of innovative technology use is higher for assignments in the first sample (2.29 innovative technologies, of which 1.33 are newly introduced) than in the second sample (0.783 innovative technologies). Thus, much of the difference in the average number of technologies that are used in each sample is accounted for by newly introduced technologies. In contrast, average engineer innovative technology experience is similar between the two subsamples, with a mean value of 3.55 for the first sample and 3.50 for the second sample. This suggests that individual engineers on average are equally familiar with innovative technologies in the two samples, and that whether units introduce new technologies is not correlated with engineers' expertise.

Instead, as explained earlier, engineers' innovative technology expertise may help units implement new technologies.

Table 1 reports descriptive statistics for the two subsamples, and the online supplement reports correlation coefficients for each subsample. Table 4 reports the OLS and instrumental variables results for the two subsamples. For ease of presentation, we report results only for the models that include the interaction term. In what follows, we concentrate on the instrumental variables results, which are reported in model 8 (new technology introduction) and model 10 (no new technology introduction).[16] Figures 2 and 3 display the estimated interaction effects for the two models graphically.

For the subsample that had no new technology introductions (model 10), for the three variables of interest, the signs of the coefficient estimates are the same as those for the full sample and are highly statistically significant. The coefficient estimate on unit innovative technology use is approximately twice that in the full sample, the coefficient estimate on engineer innovative technology experience is approximately half that in the full sample, and the coefficient estimate on the interaction term is approximately the same as in the full sample. The positive coefficient on the interaction effect suggests that individual engineer technology-related experience and unit innovative technology use are substitutes.

In contrast, in model 8 for the subsample when units introduce new technologies, the signs on all three coefficients are reversed, and the coefficient on engineer innovative technology experience is not statistically significant at conventional levels. The estimated coefficients on unit technology use are statistically significantly different between the two subsamples ($p<0.00015$), and the coefficients on the interaction term differ as well ($p<0.036$), but the coefficients do not differ significantly for engineer innovative technology experience (tests were performed using the *metaparm* routine in Stata).

[16] In the new technology introduction subsample, one country unit has only one observation. Because the *xtivreg2* routine does not include a constant term, the routine dropped this observation from the analysis. In model 8, as an instrument we interact prior unit technology use with prior innovative technology specialization per engineer rather than managerial experience, because the latter interaction does not perform well as an instrument in the new technology introduction subsample. Both models 8 and 10 pass the underidentification test (Kleibergen-Papp rk LM statistic value of 20.041with $p=0.0002$ in model 8 and a value of 27.075 with $p=0.0000$ in model 10), the weak identification test (Cragg-Donald Wald statistic of 7.441 in model 8 and 6.870 in model 10, which exceed the Stock-Yogo critical value of 6.61 in models 8 and 10 for 10% maximal bias and $p<0.05$), and the overidentification test (Hansen J statistic value of 1.322 with $p=0.5164$ in model 8 and a value of 1.033 with $p=0.5967$ in model 10).

In model 8, the positive and statistically significant coefficient on unit innovative technology use indicates that the use of an additional innovative technology is associated with higher costs per meter. This suggests that, consistent with prior literature, performance may suffer when units introduce new process technologies due to difficulties in deploying unfamiliar techniques (Argote, 2013). The lack of statistical significance on the coefficient for engineer innovative technology experience also suggests that engineers who have had experience with a larger number of technologies, and are therefore more likely to have prior experience with the newly introduced technologies, may have less difficulty. In addition, the negative coefficient on the interaction term suggests that the interaction between individual engineer technology experience and unit innovative technology use is positively related to performance (lower costs per meter), and the two are complements. When units introduce new technologies, the greater the number of innovative technologies with which an engineer has experience, then the greater is the likelihood that an engineer has prior knowledge of the newly introduced technologies – which could help the unit implement the technologies more effectively. Notably, during assignments when units introduced new technologies, individual engineers on average had prior experience with 0.93 of the newly introduced innovative technologies used by their units, out of an average of 1.33 innovative technologies introduced per unit.

Discussion and Conclusion

Knowledge is a crucial source of competitive advantage and knowledge transfer is a fundamental practice for achieving competitive advantage. Individual human capital represents a natural object of transfer. In fact, prior research has argued that firms can overcome impediments to knowledge transfer through the transfer of individuals across units, including through intra-firm geographic mobility. However, a relatively small amount of empirical research has investigated the effects on performance, which depend importantly on the interactive effects of the expertise of individuals and factors at the organization-unit level. Given the relatively small amount of prior research on the effect on organizational performance of intra-firm knowledge transfer through the transfer of individuals, rather than propose formal hypotheses, in

this study we asked three interrelated research questions.: (1) whether intra-firm transfer of knowledge through the transfer of individuals with innovative technology-related expertise improves the performance of the organizational units to which the individuals move, (2) whether the knowledge of these individuals is a complement or substitute for organization-level factors in the effect on organizational performance, and (3) whether the answers to these questions depend on the use of new versus familiar technologies.

Our study provides several findings of note. First, the transfer of knowledge through the transfer of employees to geographically-dispersed organizational units reduces costs substantially, both as a percentage of costs and in dollar value. Although the engineers in this study are skilled employees, they are neither stars, nor at the top of the organization, nor especially powerful for other reasons. This finding offers support for the argument in the microfoundations (Felin, Foss, and Ployhardt, 2015) and strategic human capital (Nyberg et al., 2014) literatures that individuals have effects on organizational performance beyond the effects of organizational capabilities. The results also show at a granular level that multinational firms can benefit significantly from the transfer of knowledge through the internal transfer of employees.

In addition, our findings shed light on the mixed evidence on whether the expertise of individuals is a complement or substitute for organization level factors by unpacking conditions under which each may hold. Although it seems natural to assume that individual expertise complements organizational factors in the effect on organizational performance, instead we find that these are substitutes in the full sample of job assignments. Further investigation reveals that this result is driven by the subsample where organizational units do not introduce new innovative technologies. When units rely entirely on innovative technologies with which they are already familiar, the innovative technology expertise of engineers may be duplicative to some extent, leading to a substitution effect. In this situation, the use of one input to production – such as familiar technology – marginally decreases the benefit for organizational performance of another input – such as an engineer's technology-related expertise (Hess and Rothaermel, 2011).

In contrast, the innovative technology expertise of individual engineers complements a unit's use of innovative technologies in the subsample where units introduce new technologies. This finding is consistent with the suggestion in the strategic human capital literature that individual and organization-level

factors are complements when the workflow depends on the knowledge of individuals (Crocker and Eckhardt, 2014), as may occur during well drilling when individual engineers have expertise in deploying an innovative technology that the unit has not used in the past.

Prior research has proposed that whether individual human capital and organization-level factors are substitutes or complements may depend on the pre-existing competences of the firm and its relationship to the human capital of individuals (Rothaermel and Hess, 2007). Little subsequent research has investigated this issue, and our findings suggest that individual and organization-level factors may have a complementary effect on organizational performance when the organization seeks to acquire new competences about which individuals possess relevant knowledge. Thus, individuals who bring novel expertise to their units may be important vehicles for breaking organization-level routines, promoting organizational learning, and building new competences. In addition, our study provides further evidence that the movement of experts helps to diffuse knowledge within the organization (Greenwood et al., 2019). These findings have implications for the microfoundations literature (Felin et al., 2015) and the strategic human capital literature (Nyberg et al., 2014) by showing that individual expertise may be especially important when organizational routines need to be changed or new competences built. These findings are also relevant for multinational firms, which often transfer employees across geographic units, and for multidivisional firms that redeploy resources such as personnel with specific technical expertise across businesses (Levinthal and Wu, 2010).

Limitations and future research

Our study has several limitations. Most notably, the data come from a single large company in one industry, and we do not know the extent to which the findings generalize. Studies of other firms in other industries would be helpful. In addition, although the study benefited from unique data on the technology-related experience of individual engineers, the data did not enable us to conduct an analysis of technology use and performance at the project (well or oil field) level. As a consequence, we could not link individual expertise to the performance of specific projects on which the individuals worked. Project level data would be especially helpful in future research on intra-firm mobility, knowledge transfer, and resource

redeployment. In addition, the setting in our study did not lend itself to an analysis of teams (as opposed to organizational units or single individuals), which would be helpful to investigate in future research.

Additional research would also be helpful to further disentangle the selection and treatment effects of knowledge transfer through individuals, which is particularly important for the literature on intra-organizational mobility as well as for the literature on resource redeployment. Although we used instrumental variables to control for the endogeneity of individuals' knowledge and expertise (the treatment), the instruments may have limitations. Future research could look for exogenous shocks that would help to further isolate the treatment effect. We also found that the selection effect of an organizational unit hiring an individual based on the unit's need for additional technology-related expertise did not affect the estimates of the treatment effect. However, there are other selection effects that we were unable examine due to data limitations, such as the selection of individuals into particular projects and the selection of specific technologies for projects. Project level data would be helpful in order to gain a better understanding of these types of selection issues.

Finally, our findings suggest the importance for managerial practice of taking the interaction between individual and organization-level factors into account. Whether firms obtain the full benefit of the expertise of individuals who are transferred across units depends on whether this expertise and organization-level factors in the recipient unit are complements or substitutes with respect to organizational performance. This may depend on contextual factors such as whether individuals bring knowledge about novel techniques that can help units break with the past and engage in organizational learning.

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Figure 1. Interaction Term Full Sample

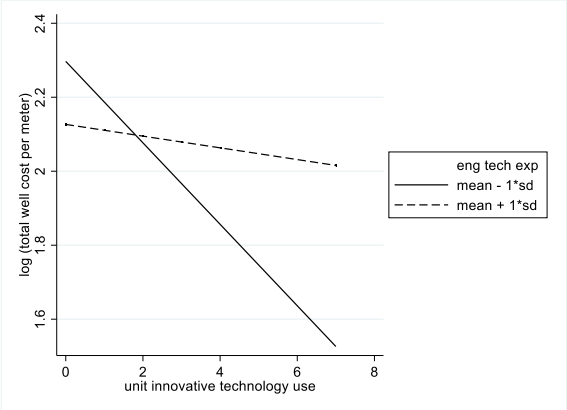

Figure 2. Interaction Term
New Technology Introduction Subsample

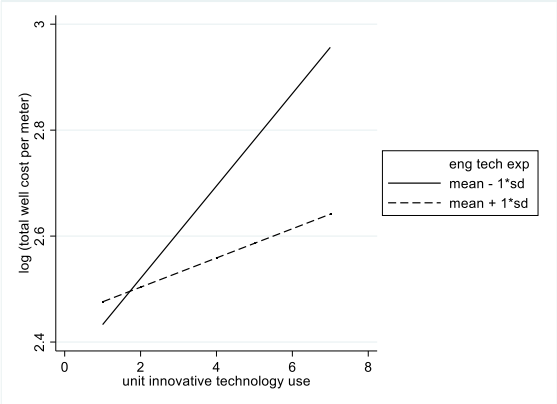

Figure 3. Interaction Term
No New Technology Introduction Subsample

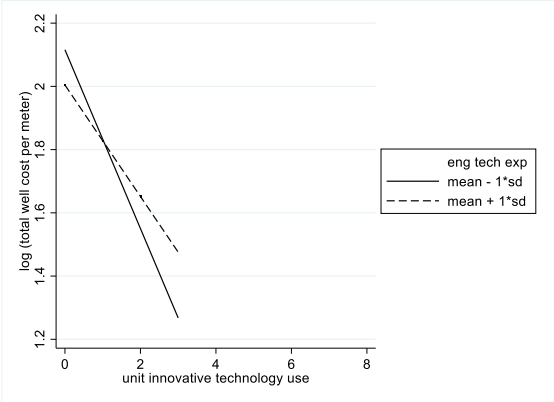

Table 1. Descriptive Statistics

	Full Sample				New Tech Introduction Subsample				No New Tech Introduction Subsample			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Total well cost per meter	9449.38	5833.66	661.95	42655.53	9342.36	3243.25	723.41	20111.63	9546.23	7437.04	661.95	42655.53
log(Total well cost per meter)	8.91	0.78	6.50	10.66	9.06	0.46	6.58	9.91	8.78	0.97	6.50	10.66
Experience in HQ	0.24	0.43	0	1	0.15	0.36	0	1	0.32	0.47	0	1
Exp. with different reserve types	4.10	1.19	0	5	4.28	0.93	0	5	3.94	1.37	0	5
Offshore and onshore experience	0.38	0.49	0	1	0.36	0.48	0	1	0.40	0.49	0	1
Days on assignment	186.26	178.40	1	1613	180.04	169.68	4	1613	191.88	185.82	1	1400
log(Days on assignment)	4.81	0.96	0.69	7.39	4.79	0.94	1.61	7.39	4.82	0.98	0.69	7.24
Seniority level	7.33	1.06	4	11	7.43	1.03	4	11	7.24	1.08	4	10
Seniority potential	2.85	0.75	1	4	2.87	0.75	1	4	2.84	0.74	1	4
Total time in firm	1600.01	1386.29	1	10637	1496.02	1324.89	1	8761	1694.12	1433.49	1	10637
log(Total time in firm)	6.93	1.14	0.69	9.27	6.90	1.05	0.69	9.08	6.96	1.23	0.69	9.27
Prior experience outside of firm	0.57	0.50	0	1	0.55	0.50	0	1	0.58	0.49	0	1
Size (# of wells drilled)	10.02	12.01	1	120	12.24	9.39	1	120	8.01	13.66	1	98
log(# of wells drilled)	2.04	0.82	0.69	4.80	2.39	0.64	0.69	4.80	1.72	0.83	0.69	4.60
Top international drilling contractor	1.95	2.98	0	29	2.17	2.68	0	16	1.75	3.22	0	29
Total well cost (million $)	289.54	252.53	5.74	1701.38	412.13	259.25	12.30	1701.38	178.59	186.46	5.74	1383.71
log(Total well cost)	5.21	1.08	1.91	7.44	5.75	0.87	2.59	7.44	4.72	1.01	1.91	7.23
Exploration well	0.96	1.71	0	18	1.31	1.74	0	11	0.65	1.61	0	18
Offshore rig	6.62	7.89	0	83	9.72	7.69	0	83	3.81	6.96	0	63
Total non-productive days	111.19	114.62	0.40	737.06	145.60	135.83	0.85	737.06	80.06	79.35	0.40	461.84
log(Total non-productive days)	4.27	1.01	0.34	6.60	4.61	0.87	0.62	6.60	3.95	1.03	0.34	6.14
Oil price in start year	81.33	18.52	24.93	106.65	75.80	15.53	33.31	106.65	86.34	19.56	24.93	106.65
Job spec: completion/integration	0.29	0.45	0	1	0.33	0.47	0	1	0.25	0.43	0	1
Job spec: commercial	0.02	0.13	0	1	0.02	0.13	0	1	0.02	0.12	0	1
Job spec: other engineering	0.04	0.20	0	1	0.04	0.19	0	1	0.04	0.21	0	1
Co-worker high level innovative technology experience	0.26	0.44	0	1	0.24	0.43	0	1	0.27	0.44	0	1
Unit innovative technology use	1.50	1.42	0	7	2.29	1.46	1	7	0.78	0.91	0	3
Engineer innov technology exp.	3.52	2.06	0	10	3.55	1.53	0	10	3.50	2.45	0	10

Table 2. Correlation Coefficients Full Sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1 Total well cost per meter	1.00																					
2 Experience in HQ	0.07*	1.00																				
3 Exp with different reserve types	0.29*	0.18*	1.00																			
4 Off/onshore exp.	-0.13*	-0.08*	0.2*	1.00																		
5 Days on assignment	-0.08*	0.08*	-0.09*	0.01	1.00																	
6 Seniority level	0.11*	-0.01	-0.17*	-0.13*	-0.06*	1.00																
7 Seniority potential	-0.01	0.03	-0.04*	-0.13*	0.02	0.19*	1.00															
8 Total time in firm	-0.01	0.01	0.55*	0.23*	0.00	-0.38*	-0.04*	1.00														
9 Prior exp.outside firm	-0.07*	0.04*	0.12*	0.04*	0.07*	-0.32*	0.39*	0.14*	1.00													
10 Size (# of wells drilled)	-0.14*	-0.33*	0.07*	0.00	0.34*	-0.03	0.04*	0.04*	0.03	1.00												
11 Top drilling contractor	0.11*	0.03	0.07*	-0.09*	0.36*	0.00	0.02	-0.06*	0.06*	0.42*	1.00											
12 Total well cost	0.55*	-0.3*	0.26*	-0.07*	0.21*	0.05*	0.01	-0.03	0.00	0.7*	0.41*	1.00										
13 Exploration well	-0.06*	-0.13*	0.06*	-0.17*	0.16*	-0.04*	0.04*	-0.09*	0.12*	0.51*	0.43*	0.41*	1.00									
14 Offshore rig	0.21*	-0.23*	0.08*	-0.19*	0.27*	0.01	0.05*	0.01	0.01	0.7*	0.5*	0.68*	0.46*	1.00								
15 Total non-productive days	-0.08*	-0.31*	0.01	0.27*	0.29*	-0.03	-0.03	-0.07*	0.1*	0.59*	0.33*	0.55*	0.38*	0.31*	1.00							
16 Oilprice in start year	-0.04*	0.1*	-0.15*	0.12*	0.1*	0.00	-0.01	0.03	-0.11*	-0.24*	-0.1*	-0.26*	-0.31*	-0.16*	-0.13*	1.00						
17 Job spec.: comp./ integration	0.07*	0.09*	0.06*	-0.06*	0.05*	0.13*	0.2*	0.07*	0.2*	0.01	0.00	0.03	-0.06*	0.03	-0.06*	-0.02	1.00					
18 Job spec.: commercial	0.01	-0.03	0.03	0.06*	0.03	-0.06*	-0.07*	0.05*	0.02	0.01	0.01	0.01	-0.04*	0.01	0.02	-0.01	-0.08*	1.00				
19 Job spec.: other engineering	0.05*	-0.05*	-0.07*	-0.05*	-0.04*	0.09*	0.05*	-0.07*	0.00	0.01	0.04*	0.06*	0.09*	0.04*	0.02	-0.07*	-0.13*	-0.03	1.00			
20 Co-worker high level innov tech exp	0.27*	-0.32*	0.17*	0.02	-0.13*	0.03	-0.02	0.07*	-0.07*	0.02	-0.05*	0.25*	-0.06*	0.11*	-0.12*	0.12*	0.02	0.01	0.01	1.00		
21 Unit innov technology use	0.25*	-0.17*	0.2*	0.06*	0.03	0.05*	-0.02	-0.12*	0.08*	0.28*	0.19*	0.54*	0.42*	0.22*	0.44*	-0.3*	-0.01	-0.01	0.1*	0.25*	1.00	
22 Engineer innov technology exp	0.26*	0.34*	0.66*	0.37*	-0.07*	-0.22*	-0.04*	0.46*	0.14*	-0.08*	-0.04*	0.13*	-0.14*	-0.03	0.00	0.06*	0.08*	0.02	-0.05*	0.24*	0.2*	1.00

* $p<0.05$ Variables in log form: days on assignment, total time in firm, size, total well cost, total non-productive days

Table 3. Organizational Performance: Log(Total Well Cost per Meter)

	M1: OLS	M2: OLS	M3: IV	M4: IV	M5: OLS	M6: IV
Experience in HQ	-0.0034	0.0129	0.0500*	0.0980***	-0.0144	0.0618*
	(0.0292)	(0.0229)	(0.0223)	(0.0280)	(0.0168)	(0.0314)
Experience with different reserve types	-0.0241*	-0.0228*	-0.0153***	-0.0120**	-0.0140*	-0.0061
	(0.0091)	(0.0084)	(0.0041)	(0.0043)	(0.0061)	(0.0043)
Offshore and onshore experience	0.0258*	0.0287*	0.0413***	0.0453***	0.0152	0.0348**
	(0.0123)	(0.0135)	(0.0109)	(0.0117)	(0.0117)	(0.0116)
Days on assignment[a]	0.0144	0.0150	0.0135***	0.0160***	0.0069	0.0058
	(0.0125)	(0.0124)	(0.0039)	(0.0041)	(0.0190)	(0.0050)
Seniority level	-0.0017	-0.0029	-0.0040	-0.0080*	-0.0024	-0.0048+
	(0.0042)	(0.0039)	(0.0029)	(0.0031)	(0.0043)	(0.0027)
Seniority potential	-0.0028	-0.0025	-0.0024	-0.0011	-0.0007	-0.0004
	(0.0036)	(0.0042)	(0.0038)	(0.0039)	(0.0034)	(0.0036)
Total time in firm[a]	0.0188+	0.0185*	0.0245***	0.0221***	0.0098+	0.0148***
	(0.0093)	(0.0087)	(0.0036)	(0.0039)	(0.0048)	(0.0033)
Prior experience outside of firm	0.0112	0.0083	0.0130*	0.0026	0.0030	0.0041
	(0.0071)	(0.0066)	(0.0061)	(0.0068)	(0.0071)	(0.0063)
Size (# of wells drilled)[a]	-0.9492***	-0.9503***	-0.9442***	-0.9459***	-0.8623***	-0.8632***
	(0.0816)	(0.0801)	(0.0142)	(0.0146)	(0.0697)	(0.0156)
Top international drilling contractor	0.0035	0.0043*	0.0027*	0.0050***	0.0032	0.0034*
	(0.0024)	(0.0019)	(0.0014)	(0.0015)	(0.0027)	(0.0014)
Total well cost[a]	0.8482***	0.8477***	0.8430***	0.8455***	0.7313***	0.7365***
	(0.0966)	(0.0954)	(0.0112)	(0.0114)	(0.0821)	(0.0134)
Exploration well	-0.0053	-0.0010	-0.0091*	0.0085	-0.0015	-0.0011
	(0.0109)	(0.0085)	(0.0041)	(0.0065)	(0.0081)	(0.0046)
Offshore rig	0.0054	0.0053	0.0055***	0.0051***	0.0033	0.0031***
	(0.0045)	(0.0045)	(0.0010)	(0.0010)	(0.0032)	(0.0008)
Total non-productive days[a]	-0.0602	-0.0595	-0.0582***	-0.0547***	0.0065	0.0084
	(0.0513)	(0.0514)	(0.0079)	(0.0080)	(0.0306)	(0.0064)
Oil price in start year	-0.0005	-0.0005	-0.0003	-0.0004	-0.0003	-0.0002
	(0.0007)	(0.0007)	(0.0002)	(0.0002)	(0.0010)	(0.0002)
Job specification: completion and integration	-0.0092*	-0.0084*	-0.0068	-0.0044	-0.0102	-0.0083
	(0.0039)	(0.0037)	(0.0056)	(0.0059)	(0.0065)	(0.0054)
Job specification: commercial	0.0103	0.0145	0.0094	0.0243	0.0054	0.0099
	(0.0104)	(0.0101)	(0.0191)	(0.0206)	(0.0046)	(0.0143)
Job specification: other engineering	0.0086	0.0112	0.0077	0.0177	-0.0023	-0.0012
	(0.0075)	(0.0075)	(0.0136)	(0.0139)	(0.0051)	(0.0115)
Co-worker high level of innov tech exper	-0.0474	-0.0538	-0.0404***	-0.0589***	0.0092	0.0036
	(0.0521)	(0.0507)	(0.0097)	(0.0114)	(0.0311)	(0.0104)
Unit innovative technology use	-0.0373	-0.0656**	-0.0315*	-0.1435***	-0.0337+	-0.0603**
	(0.0284)	(0.0221)	(0.0126)	(0.0364)	(0.0170)	(0.0230)
Engineer innov technology experience	0.0008	-0.0073*	-0.0161**	-0.0413***	-0.0017	-0.0269**
	(0.0056)	(0.0034)	(0.0054)	(0.0093)	(0.0041)	(0.0096)
Unit technology x engineer technology		0.0066*		0.0228***	0.0051**	0.0116**
		(0.0026)		(0.0067)	(0.0018)	(0.0045)
Constant	6.7210***	6.7492***			6.8862***	
	(0.1996)	(0.1956)			(0.1891)	
Year Dummies	YES	YES	YES	YES	YES	YES
Unit (Country) Fixed Effect	YES	YES	YES	YES	YES	YES
Observations	3208	3208	3208	3208	2408	2408
R^2	0.851	0.853	0.848	0.838	0.871	0.865
Adjusted R^2	0.850	0.852	0.846	0.835	0.869	0.862

Standard errors in parentheses; + p<0.10, * p<0.05, ** p<0.01, *** p<0.001 [a] variable in log form

Table 4. New Technology and No New Technology Introduction Subsamples

	New Tech Intro		No New Tech Intro	
	M7: OLS	M8: IV	M9: OLS	M10: IV
Experience in HQ	0.0158	-0.0124	-0.0122	0.0359
	(0.0235)	(0.0347)	(0.0151)	(0.0264)
Experience with different reserve types	0.0000	0.0055	-0.0130	-0.0047
	(0.0016)	(0.0056)	(0.0079)	(0.0064)
Offshore and onshore experience	0.0115	0.0076	0.0316+	0.0083
	(0.0126)	(0.0118)	(0.0155)	(0.0176)
Days on assignment[a]	0.0009	-0.0122	0.0038	-0.0024
	(0.0124)	(0.0075)	(0.0134)	(0.0062)
Seniority level	-0.0012	-0.0004	-0.0030	-0.0089+
	(0.0024)	(0.0029)	(0.0044)	(0.0046)
Seniority potential	0.0009	-0.0037	-0.0061+	-0.0061
	(0.0021)	(0.0040)	(0.0034)	(0.0056)
Total time in firm[a]	0.0043	0.0046	0.0156*	0.0122*
	(0.0045)	(0.0047)	(0.0071)	(0.0056)
Prior experience outside of firm	-0.0049+	-0.0041	0.0112**	0.0081
	(0.0027)	(0.0066)	(0.0034)	(0.0090)
Size (# of wells drilled)[a]	-0.7758***	-0.7235***	-0.9094***	-0.8527***
	(0.0778)	(0.0331)	(0.0395)	(0.0257)
Top international drilling contractor	-0.0021	-0.0044+	0.0129**	0.0129***
	(0.0014)	(0.0027)	(0.0035)	(0.0021)
Total well cost[a]	0.7355***	0.6922***	0.8049***	0.8148***
	(0.0842)	(0.0218)	(0.0480)	(0.0188)
Exploration well	-0.0130	-0.0436***	0.0144+	0.0244***
	(0.0096)	(0.0117)	(0.0073)	(0.0062)
Offshore rig	0.0063***	0.0073***	-0.0060**	-0.0079***
	(0.0011)	(0.0013)	(0.0016)	(0.0014)
Total non-productive days[a]	-0.0327	-0.0233*	-0.0516	-0.0356**
	(0.0351)	(0.0105)	(0.0302)	(0.0123)
Oil price in start year	0.0015***	0.0017***	-0.0010	-0.0005
	(0.0003)	(0.0003)	(0.0007)	(0.0004)
Job specification: completion and integration	-0.0011	0.0061	0.0056	-0.0021
	(0.0037)	(0.0059)	(0.0064)	(0.0098)
Job specification: commercial	0.0260*	0.0241+	0.0087	0.0540+
	(0.0119)	(0.0146)	(0.0199)	(0.0309)
Job specification: other engineering	-0.0082	-0.0089	-0.0055	0.0252
	(0.0083)	(0.0138)	(0.0082)	(0.0232)
Co-worker high level of innov tech exper	0.0298*	0.0400***	-0.1319***	-0.0769**
	(0.0119)	(0.0116)	(0.0304)	(0.0245)
Unit innovative technology use	-0.0196+	0.1208**	-0.0590**	-0.3056***
	(0.0093)	(0.0457)	(0.0197)	(0.0790)
Engineer innov technology experience	-0.0143+	0.0306	-0.0064	-0.0228**
	(0.0070)	(0.0197)	(0.0038)	(0.0071)
Unit technology x engineer technology	0.0062**	-0.0182*	0.0035+	0.0218***
	(0.0020)	(0.0088)	(0.0019)	(0.0064)
Constant	6.6467***		6.9268***	
	(0.2652)		(0.1365)	
Year Dummies	YES	YES	YES	YES
Unit (Country) Fixed Effect	YES	YES	YES	YES
Observations	1524	1523	1684	1684
R^2	0.929	0.890	0.850	0.779
Adjusted R^2	0.928	0.887	0.847	0.773

Standard errors in parentheses; + p<0.10, * p<0.05, ** p<0.01, *** p<0.001 [a] variable in log form

ONLINE SUPPLEMENT

Sample Selection Model

To conduct a formal Heckman type test for selection bias in the presence of endogenous regressors, we use the procedure developed by Semykina and Wooldridge (2010) for panel data with fixed effects. This procedure entails estimating a first stage probit selection model using the Mundlak (1978) procedure of including time-averaged variables to control for fixed effects, and then including the inverse Mills ratio (IMR) from this model in a 2SLS model. If the estimated coefficient on the IMR is statistically significant, this indicates the presence of sample selection bias.

A probit model cannot be estimated using a standard fixed effects model due to the incidental parameters problem. We are also unable to use the *probitfe* program in Stata that corrects for this problem, because our data are not organized as a panel. Instead, each observation is at the job assignment level. We therefore rely on the Mundlak (1978) procedure of including time-averaged values of the right-hand side variables in the probit model to control for unit fixed effects. Per Semykina and Wooldridge (2010), the probit selection model must include an additional exogenous variable that serves as an instrument as well as all of the exogenous variables in the 2SLS model, including the instruments used in that model; the probit model cannot include any variables that are endogenous in the 2SLS model (see also Wooldridge, 2002, pp. 568-9). The inverse Mills ratio estimated from the probit model is then included in the 2SLS model, and the additional instrument in the selection equation is included as an instrument in the 2SLS estimation together with the other instruments in that model. Because this is a test rather than a correction for sample selection bias, it is not necessary to adjust the standard errors in the 2SLS model to account for the inverse Mills ratio being a predicted value derived from the probit selection model (Semykina and Wooldridge, 2010).

To construct the sample for the probit selection model, we organize the data by year. For each year, we include all engineers who began a new assignment during that year as well as all engineers who were working in OILCOMP on a continuing assignment during that year (and therefore could potentially have been hired into available positions but were not). The dependent variable in the first stage probit equation, *engineer newly hired*, measures in each year whether or not an engineer was newly hired during that year by the unit in which the engineer was working at the end of the year. For

each year, engineers who were hired into a unit during that year receive a value of 1 for the dependent variable and engineers who were not hired into any unit during that year receive a value of 0. Although Semykina and Wooldridge (2010) recommend estimating the IMR separately for each year, we do not have enough observations per year to enable the annual probit models to converge. Instead, we include all years together in the probit model, compute the time-averaged values per unit of the right-hand side variables following Mundlak (1978), and include these variables in the model.

As an instrument in the probit model, we use the innovative technology expertise of the engineers in each unit in the prior year, *prior year engineer innovative technology experience per unit*. The innovative technology expertise that a unit has among the engineers working in the unit might affect its decision to hire. For example, if the engineers in a unit have expertise in fewer innovative technologies, the unit might seek to hire engineers who have greater breadth of expertise. The instrumental variable is constructed as the count of the number of different innovative technologies used in the past by all engineers working in a unit in the prior year, which is similar to the *engineer innovative technology experience* variable except that the new variable measures engineer experience at the unit level and in the prior year rather than the current year. The new variable would not directly affect well drilling costs in the current year because the engineers working in each unit differ from year to year.

Table A1 reports the results. In the first stage model, the coefficient on *prior year engineer innovative technology experience per unit* is negative and statistically significant, indicating that units with less innovative technology expertise among its engineers in the prior year are more likely to hire. However, in the second stage 2SLS model, the inverse Mills ratio is not statistically significant (p-value=0.1187) and the explanatory variables are highly significant with the same signs and similar coefficient estimates to the original 2SLS model, suggesting that sample selection bias does not affect our estimates.[17]

[17] The 2SLS model passes the underidentification test (Kleibergen-Papp rk LM statistic value of 48.047, p=0.000), the weak identification test (based on Cragg-Donald Wald statistic of 8.460, which exceeds the Stock-Yogo critical value of 7.77 for 10% maximal bias and p<0.05), and the overidentification test (the Hansen J statistic is 3.90, p=0.2724).

REFERENCES

Mundlak Y (1978) On the pooling of time series and cross section data. *Econometrica* 46: 69-85.

Semykina A, Wooldridge JM (2010) Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics* 157: 375-380.

Table A1. Two-stage Sample Selection Estimates

	Stage 1 - PROBIT Engineer newly hired	Stage 2 - IV 2SLS Log(total well cost per meter)
Experience in HQ	-0.0281	0.1011***
	(0.1166)	(0.0269)
Experience with different reserve types	-0.0298	-0.0132**
	(0.0291)	(0.0044)
Offshore and onshore experience	0.0284	0.0489***
	(0.0761)	(0.0117)
Days on assignment[a]	-0.4403***	0.0082
	(0.0431)	(0.0071)
Seniority level	-0.0096	-0.0078*
	(0.0256)	(0.0031)
Seniority potential	0.0124	-0.0013
	(0.0343)	(0.0039)
Total time in firm[a]	0.0323	0.0245***
	(0.0272)	(0.0040)
Prior experience outside of firm	-0.0161	0.0037
	(0.0556)	(0.0067)
Size (# of wells drilled)[a]	0.1992+	-0.9483***
	(0.1054)	(0.0143)
Top international drilling contractor	-0.0361***	0.0044**
	(0.0096)	(0.0016)
Total well cost[a]	0.0014	0.8461***
	(0.0755)	(0.0109)
Exploration well	0.0326	0.0079
	(0.0207)	(0.0066)
Offshore rig	0.0086	0.0049***
	(0.0055)	(0.0010)
Total non-productive days[a]	-0.2637***	-0.0589***
	(0.0483)	(0.0093)
Oil price in start year	0.0197***	-0.0000
	(0.0019)	(0.0004)
Job specification: completion and integration	-0.0473	-0.0047
	(0.0510)	(0.0059)
Job specification: commercial	-0.0670	0.0214
	(0.1615)	(0.0207)
Job specification: other engineering	0.1516	0.0221
	(0.1153)	(0.0137)
Co-worker high level of innov tech exper	0.7369***	-0.0478***
	(0.0909)	(0.0118)
Prior year engineer innov technology experience per unit	-0.0388*	
	(0.0162)	
# of times unit used innovative technologies in prior year	-0.1404***	
	(0.0359)	
Managerial experience	0.0040	
	(0.0159)	
# previous times engineer used his/her most frequently used technology	-0.0049	
	(0.0114)	
Experience with complex wells	-0.0087	
	(0.0540)	
# of times unit used innov technologies in prior year x managerial experience	0.0016	
	(0.0072)	
Unit innovative technology use		-0.1336***
		(0.0372)
Engineer innov technology experience		-0.0420***
		(0.0090)

Unit technology x engineer technology		0.0217**
		(0.0067)
Inverse Mills ratio		0.1635
		(0.1187)
Constant	8.7659	
	(6.2296)	
Year dummies	YES	YES
Unit (Country) fixed effect	NO	YES
Average variables	YES	NO
Observations	4612	3197
Pseudo loglikelihood	-2379.8731	
R^2		0.840
Adjusted R^2		0.837

Standard errors in parentheses: $^{+}$ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Subsample Correlation Coefficients

Table A2. Correlation Coefficients New Technology Introduction Subsample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1 Total well cost per meter	1.00																					
2 Experience in HQ	-0.5*	1.00																				
3 Exp with different reserve types	0.21*	0.12*	1.00																			
4 Off/onshore exp.	-0.21*	0.00	0.02	1.00																		
5 Days on assignment	-0.27*	0.11*	-0.15*	0.1*	1.00																	
6 Seniority level	0.08*	-0.01	-0.07*	-0.07*	-0.03	1.00																
7 Seniority potential	-0.03	0.04	0.00	-0.16*	0.02	0.17*	1.00															
8 Total time in firm	-0.01	-0.1*	0.44*	0.13*	-0.06*	-0.29*	0.08*	1.00														
9 Prior exp.outside firm	-0.11*	0.09*	0.11*	0.01	0.12*	-0.29*	0.4*	0.19*	1.00													
10 Size (# of wells drilled)	0.12*	-0.37*	-0.13*	-0.14*	0.5*	-0.04	0.07*	0.02	0.04	1.00												
11 Top drilling contractor	0.03	0.00	-0.07*	0.04	0.45*	0.00	0.00	-0.16*	0.15*	0.22*	1.00											
12 Total well cost	0.64*	-0.53*	0.05*	-0.21*	0.24*	0.02	0.01	-0.06*	0.01	0.77*	0.31*	1.00										
13 Exploration well	0.04	-0.09*	-0.02	-0.29*	0.3*	-0.02	0.04	-0.15*	0.15*	0.39*	0.47*	0.44*	1.00									
14 Offshore rig	0.31*	-0.32*	-0.09*	-0.41*	0.28*	0.01	0.12*	0.03	0.02	0.74*	0.26*	0.64*	0.47*	1.00								
15 Total non-productive days	-0.09*	-0.14*	-0.18*	0.35*	0.54*	-0.03	-0.11*	-0.15*	0.1*	0.37*	0.5*	0.35*	0.22*	0.09*	1.00							
16 Oilprice in start year	-0.04	0.18*	-0.01	0.16*	0.03	0.03	-0.01	0.09*	-0.1*	-0.17*	-0.14*	-0.21*	-0.38*	-0.15*	0.02	1.00						
17 Job spec.: comp./ integration	0.03	0.05	0.06*	-0.09*	-0.01	0.14*	0.26*	0.12*	0.28*	-0.01	-0.02	0.00	-0.04	0.02	-0.1*	0.02	1.00					
18 Job spec.: commercial	0.01	-0.04	0.01	0.08*	0.00	0.01	-0.06*	0.03	0.02	0.00	0.00	0.00	-0.03	0.00	0.05	-0.01	-0.09*	1.00				
19 Job spec.: other engineering	0.03	-0.07*	-0.07*	-0.14*	0.01	0.13*	0.09*	-0.08*	0.05*	0.05*	0.13*	0.09*	0.19*	0.1*	0.02	-0.09*	-0.14*	-0.03	1.00			
20 Co-worker high level innov tech exp	0.39*	-0.24*	0.22*	-0.36*	-0.23*	0.03	0.03	0.06*	-0.05*	0.1*	-0.17*	0.31*	0.1*	0.16*	-0.37*	-0.03	0.07*	-0.03	0.00	1.00		
21 Unit innov technology use	0.08*	0.05*	0.09*	-0.06*	0.16*	-0.03	-0.05	-0.21*	0.17*	0.05*	0.39*	0.29*	0.6*	0.01	0.34*	-0.28*	-0.06*	-0.03	0.13*	0.16*	1.00	
22 Engineer innov technology exp	0.00	0.38*	0.56*	0.16*	-0.13*	-0.19*	0.02	0.38*	0.21*	-0.2*	-0.11*	-0.11*	-0.16*	-0.2*	-0.1*	0.23*	0.07*	-0.01	-0.07*	0.11*	0.16*	1.00

* $p<0.05$ Variables in log form: days on assignment, total time in firm, size, total well cost, total non-productive days

Table A3. Correlation Coefficients No New Technology Introduction Subsample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1 Total well cost per meter	1.00																					
2 Experience in HQ	0.31*	1.00																				
3 Exp with different reserve types	0.29*	0.26*	1.00																			
4 Off/onshore exp.	-0.09*	-0.16*	0.32*	1.00																		
5 Days on assignment	-0.01	0.06*	-0.06*	-0.06*	1.00																	
6 Seniority level	0.1*	0.01	-0.25*	-0.17*	-0.08*	1.00																
7 Seniority potential	-0.01	0.03	-0.07*	-0.09*	0.03	0.2*	1.00															
8 Total time in firm	0.00	0.07*	0.63*	0.3*	0.05	-0.45*	-0.13*	1.00														
9 Prior exp.outside firm	-0.06*	0.00	0.14*	0.07*	0.02	-0.34*	0.38*	0.1*	1.00													
10 Size (# of wells drilled)	-0.36*	-0.23*	0.07*	0.12*	0.3*	-0.1*	0.02	0.07*	0.05*	1.00												
11 Top drilling contractor	0.12*	0.06*	0.13*	-0.18*	0.3*	-0.01	0.03	0.01	-0.01	0.55*	1.00											
12 Total well cost	0.52*	-0.06*	0.3*	0.06*	0.24*	0.01	0.00	0.01	0.03	0.54*	0.51*	1.00										
13 Exploration well	-0.17*	-0.11*	0.07*	-0.04	0.04	-0.11*	0.03	-0.03	0.11*	0.56*	0.4*	0.32*	1.00									
14 Offshore rig	0.11*	-0.07*	0.11*	0.02	0.31*	-0.05*	-0.02	0.01	0.02	0.6*	0.74*	0.6*	0.38*	1.00								
15 Total non-productive days	-0.17*	-0.34*	0.04	0.27*	0.14*	-0.08*	0.03	0.00	0.13*	0.63*	0.22*	0.55*	0.45*	0.32*	1.00							
16 Oilprice in start year	0.02	-0.03	-0.17*	0.09*	0.15*	0.02	0.00	-0.01	-0.15*	-0.13*	-0.05*	-0.11*	-0.18*	0.01	-0.08*	1.00						
17 Job spec.: comp./ integration	0.06*	0.17*	0.04	-0.03	0.1*	0.1*	0.14*	0.04	0.14*	-0.05*	0.01	-0.02	-0.12*	-0.04	-0.08*	-0.01	1.00					
18 Job spec.: commercial	0.00	-0.01	0.04	0.04	0.05*	-0.13*	-0.08*	0.06*	0.02	0.01	0.01	0.02	-0.05*	0.02	-0.01	-0.02	-0.07*	1.00				
19 Job spec.: other engineering	0.07*	-0.04	-0.06*	0.02	-0.08*	0.06*	0.02	-0.07*	-0.04	0.00	-0.02	0.07*	0.02	0.00	0.03	-0.07*	-0.12*	-0.03	1.00			
20 Co-worker high level innov tech exp	0.25*	-0.39*	0.16*	0.34*	-0.04	0.04	-0.07*	0.08*	-0.08*	0.00	0.03	0.29*	-0.2*	0.1*	0.08*	0.22*	-0.02	0.04	0.02	1.00		
21 Unit innov technology use	0.32*	-0.24*	0.24*	0.33*	-0.13*	0.04	-0.02	-0.02	0.06*	0.12*	-0.07*	0.54*	0.07*	0.06*	0.38*	-0.11*	-0.08*	0.02	0.13*	0.56*	1.00	
22 Engineer innov technology exp	0.34*	0.34*	0.71*	0.49*	-0.03	-0.25*	-0.08*	0.5*	0.11*	-0.04	-0.01	0.27*	-0.14*	0.07*	0.04	-0.01	0.09*	0.04	-0.04	0.32*	0.35*	1.00

* $p<0.05$ Variables in log form: days on assignment, total time in firm, size, total well cost, total non-productive days