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ORGANIZATIONAL ADAPTATION IN OFFSHORING: THE RELATIVE PERFORMANCE OF HOME- AND HOST-BASED LEARNING STRATEGIES

Abstract: Offshoring offers managers the promise of substantial economic benefits, but also comes with the risk of increased complexity and coordination challenges. We argue that offshoring firms must accumulate architectural knowledge in order to keep the cost of complexity and coordination of the geographically separated activities at bay. Based on a simulation model that examines the performance implications of firms' learning strategies when offshoring, we show that such knowledge accumulation can be achieved through either a home-based or a host-based learning strategy. Our analysis suggests that the relative performance of these two strategies depends on non-trivial interactions among the costs of communication, the distance to the offshoring location, and the level of noise in the firm's performance function. In particular, the difficulties of interpreting performance signals in noisy situations suggest that there are benefits of making changes to the configuration *after* the offshoring implementation (host based learning). In contrast, when coordination costs and distance dominate, the strategy of gearing the organization for offshoring *prior* to separating them across country borders prevails (home-based learning). Thus, by formalizing these two learning strategies for acquiring architectural knowledge in offshoring, we show that important contingencies can lead to significant performance trade-offs in the search for new organizational configurations that span international borders.

Keywords: Adaptation, offshoring, architectural knowledge, coordination cost, noisy search.

INTRODUCTION

As much as the benefits of offshoring have attracted a large number of multinational firms to relocate business activities to distant locations, the strategy has also introduced managers to difficult dilemmas. In particular, it has been noted that firms' value chains are subject not only to centrifugal forces encouraging geographic dispersion, but also to centripetal forces that encourage co-location of related activities (Baldwin and Venables 2013). Accordingly, many firms struggle to reap the economic returns from offshoring without getting overwhelmed by the complexity of coordinating dispersed activities across vast distances (Contractor et al. 2010, Larsen, Manning and Pedersen 2013, Srikanth and Puranam 2011). To shed light on this issue, we explore the performance implications of organizational adaptation when offshoring.

The extensive research on organizational adaptation has demonstrated that changing technologies and environments force boundedly rational problem solvers to engage in an adaptive search for satisfactory solutions to complex problems (Cyert and March 1963, Gavetti 2005, Levinthal 1997, Levinthal and March 1981, March and Simon 1958, Nelson and Winter 1982, see also Online Appendix 1 for an overview). However, as recent research shows, the ways in which firms actually engage in such processes is unclear (Baumann and Siggelkow 2014, Fleming 2001, Winter et al. 2007). In particular, the answer to the question of *when* firms should initiate adaptive search processes when they are faced with uncertainty regarding integration of separated (but interdependent) activities and the added coordination requirements across distance is not straightforward. Given that the literature streams on offshoring and adaptation remain largely disjointed, extant research provides little guidance on this question.

In an attempt to bridge these two literature streams and provide a more complete picture of how firms adapt their organizations in an international context, we build a simulation model that allows us to analyze the performance implications of different learning strategies in relation to offshoring. We embed our argument in the observation that the structure of firms' search processes has important performance effects (Bauman and Siggelkow 2014), and focus on how firms accumulate *architectural knowledge* in order to accommodate for the added coordination requirements associated with offshoring. Hence, we

emphasize that firms reconstructing their organizations in a new international setting must gain architectural knowledge regarding the interfaces within a system of complex, causally ambiguous, and imperfectly understood tasks, processes, and organizational routines.

We investigate the performance implications of two generic learning strategies that firms may employ in their approach to offshoring. First, firms can pursue a *host-based learning strategy,* in which they initiate the accumulation of architectural knowledge only *after* a relocation has taken place. Thus, firms pursuing this strategy adapt their configurations to the technological landscape on the basis of their actual offshoring experience. Second, firms can follow a *home-based learning strategy* through which they initiate the accumulation of architectural knowledge *prior* to the actual offshoring of activities. In these cases, firms accumulate architectural knowledge by experimenting with different configurations while the activities are still located in the home country. When these firms begin to offshore, they can utilize this knowledge for effective adaptation in the new location.

Received wisdom on the importance of "being prepared" would seem to favor the home-based approach. By engaging in deliberate planning and due diligence prior to offshoring (see Ansoff et al. 1970, Puranam et al. 2006), firms can gear their organizations to handle the coordinative challenges of offshoring. However, in our simulation, this intuition is not necessarily supported. On the one hand, we find that a home-based learning strategy is often associated with higher performance than a host-based learning strategy when distances and communication costs are high. As the costs of coordinating an international organization across geographical distances rise, firms can benefit from accumulating architectural knowledge prior to an international reconfiguration. As such, the benefits of "being prepared" outweigh the costs of such up-front investments. On the other hand, as the noise in the search function increases, we find that the host-based learning strategy becomes associated with higher performance than the home-based learning strategy. Noise—resulting from the uncertainty of the technologies being relocated—makes it difficult for firms to estimate the impact and consequences of an organizational reconfiguration prior to its implementation. In such situations, firms may invest in

accumulating architectural knowledge before the offshoring event, only to find that the acquired knowledge does not reflect the actual coordination challenges in the globally dispersed organization.

With this article, we contribute to the extant literature by applying the concept of organizational adaptation in the context of offshoring. In addition to building on extant, formal models of adaptation by acknowledging the roles of distance, noise, and opposing learning strategies, we extend the research on offshoring and the global distribution of work by stressing the importance of coordination costs and the need to accumulate architectural knowledge. While extant research on internationalization has often focused on the degree to which firms must adapt their strategies to serve local requirements (Lord and Ranft 2000, Makino and Delios 1996, Siegel and Larson 2009), we suggest that firms face a paradox when deciding to reconfigure internationally. More specifically, we argue that deliberate planning and due diligence (Ansoff et al. 1970, Puranam et al. 2006) through home-based learning may lead to performance-deteriorating trajectories. In this regard, our results echo those presented by Szulanski and Jensen (2006, 2008), who studied the performance effects of a replication strategy ("copying exactly") versus a local adaptation strategy when internationalizing. A key point of their research is the necessity of acknowledging the distinction between the adaptation of spatial dimensions (related to the accumulation of local market knowledge) and the adaptation of organizational dimensions (similar to accumulating architectural knowledge). However, while they focus on the immediate trade-off between pursuing architectural knowledge (replication) and local market knowledge (local adaptation), we focus on the issue of adaptation in offshoring given the complexities of disaggregating an interdependent organization, and relocating tasks and sub-components to foreign locations. Thus, in the context of noise, the difficulties of interpreting performance signals suggests that there are benefits of making changes in the configuration in the host location. In contrast, in the context of coordination costs and distance, it makes sense to gear the organization for offshoring prior to separating them across country borders.

In the following, and before introducing our theoretical background and the model itself, we discuss the dilemma inherent in offshoring adaptation through an illustrative case study of product development in Nokia Denmark (a Danish R&D subsidiary of the Nokia Corporation).

Adaptation in offshoring: The case of product development in Nokia Denmark[1]

The primary activity of Nokia Denmark in the early 2000s was the development of new mobile-phone models, including every aspect of mechanics, electro-mechanics, electronics, and software. Nokia Denmark possessed all of the competencies needed to move a new mobile phone from the initial specification to final production. The development process included designing the specifications of a new mobile phone, working with suppliers, and preparing the phone for production, after which the entire project was transferred to a production site for mass-market production.

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

Nokia Denmark had conducted many development projects over the years, and it followed the standardized process as shown in Figure 1. The various activities were organized according to five milestones that could only be reached if an assigned committee approved the development. PD0 marks the initiation of the product program; PD1 notes the product- development release (i.e., full functionality of the product); PD2 indicates the manufacturing release (i.e., full performance of the product); PD3 notes the delivery release (i.e., ready for the market); and PD4 represents the determination of product development (i.e., handover to product maintenance). Each of these cycles typically took around one year. One Nokia product development manager explained the process as follows:

> *Concept mapping focuses on creating a lot of different ideas and finding the ones with most promise. Product development is basically maturing what we have at that point—a concept. Product maintenance aims at keeping the product alive and integrating different components. We have divided the process into these parts, as each phase requires different competences and mindsets.*

Offshoring to China

[1] This illustrative case draws on primary data collected by the authors through a number of semi-structured interviews conducted with Nokia Denmark managers in 2009 and 2010 (see also Larsen and Pedersen, 2011). It should, of course, be noted that the generalizability of this case may be limited, especially when considering the broader context of the events described in this case: In 2012, the activities in Denmark were shut down and moved to other Nokia R&D sites, and in 2013, Microsoft announced that it would acquire Nokia's entire mobile phone business. Furthermore, Foxconn has a notorious reputation of poor working conditions and high suicide rates among its employees. Thus, we acknowledge that the illustrative example used here potentially bears on multiple complex issues, but retain that it also provides interesting insights that motivate the relevance of our model and simulation.

On average, Nokia Denmark conducted around eight mobile-phone development projects running in parallel. However, in 2007, the management of Nokia Denmark decided to begin offshoring parts of the process to China, where they were to be handled by Foxconn, a major multinational electronics component manufacturer. Nokia Denmark decided to offshore two of the parallel development projects, while retaining around six projects in Denmark. The move was motivated by a desire for cost savings and by the fact that Foxconn had supplied electronics components to Nokia for a number of years. As such, the two companies already had a relatively high degree of integration.

The intention of the collaboration was that the Danish organization would be responsible for development of the advanced parts of new mobile phones, while the Chinese organization would focus on more standardized parts, such as the molding and fitting of plastic components. Specifically, the responsibility for the product-development phase (PD0-PD4) was relocated to China, while product-portfolio management and product maintenance were still handled in Denmark. Consequently, the entire development function was reconfigured from being exclusively located in Denmark to become dispersed, with interdependent tasks split between Denmark and China.

Adaptation challenges

Nokia's Danish management team had little experience in offshoring knowledge-intensive and technologically sophisticated activities across such vast distances. Therefore, it had little architectural knowledge on how the offshored activities could best be re-integrated into the product-development process. The company had hoped that the foreign activities would be largely self-manageable and require minimum intervention. However, the management quickly learned that the critical interfaces between concept mapping and product maintenance in Denmark on the one hand, and product development in China on the other, presented substantial coordination challenges. In particular, safeguarding against misinterpretations and misbehavior required substantially more coordination than initially expected. According to a Nokia manager:

> *We started out with mechanics and plastic parts in China because the Chinese had the competencies and could, therefore, govern themselves. However, we quickly came to the conclusion that this did not really work. It required too much management overhead and it did*

not really free up any resources. We were still sitting here reviewing the drawings to see if they had done them properly and checking that the test results were good enough.

Therefore, although the architecture may have been effective while all of the activities were located in Denmark, the decision to relocate certain activities to China gave rise to new coordination challenges for management. For example, while the crucial interdependencies could originally be coordinated through relatively informal mechanisms, such as face-to-face meetings, the offshoring move required new architectural knowledge and the introduction of alternative mechanisms that could accompany the new configuration.

Consequently, the Danish management began to experiment with different architectural solutions, such as disaggregating the value chain in different ways, standardizing the interdependencies, and implementing new coordination mechanisms. For example, Nokia Denmark's management learned that frequent meetings and task monitoring were vital for ensuring that the products were developed as expected. They also realized that it was necessary to transfer substantially more information to China on the interfaces inherent in the mobile phones. Consequently, the Danish management decided to assign eight full-time Nokia Denmark employees to follow and monitor the offshored projects, which were handled by 30 to 50 engineers in China. The Nokia employees arranged weekly video conferences to discuss the status of each project, as well as specific technological and organizational challenges or alterations that might have arisen. Moreover, the partners met in either Denmark or China every six to eight weeks. In addition, Nokia began altering the configuration by assigning more technical responsibilities to China. Nokia Denmark soon learned that the original intention of handling the mechanical and plastic parts in China, and technical optimization in Denmark was far too costly in terms of coordinating the interfaces between the activities. Therefore, management decided to transfer parts of these activities to China.

In terms of the terminology introduced earlier in this article, Nokia Denmark's approach to the offshoring process can be categorized as an example of host-based learning. Along these lines, one Nokia manager commented:

It is really learning-by-doing. Nokia is kind of a "cowboy" company. We plunge into things, muddle our way through and eventually become wiser. There is not much design in the things we do. We go out and try, and then we adjust.

Nokia Denmark was well experienced in conducting development projects domestically. However, it embarked on the offshoring process rather abruptly without acknowledging the likely challenges of international coordination. In this respect, it is interesting to know whether Nokia Denmark would have been better off if it had diligently attempted to map out the coordinative challenges of offshoring prior to the implementation (i.e., a home-based strategy). Thus, this illustrative case gives rise to our central questions: How do firms adapt to technological landscapes in an international context? What are the performance implications of different adaption approaches?

THEORETICAL BACKGROUND

Firms engage in offshoring for a number of reasons, including a desire to access low-cost labor, talent, and markets (Manning et al. 2008). For example, Nokia Denmark's decision to offshore product development was largely driven by cost considerations. Evidently, the pursuit of offshoring strategies has been a prolific adventure for many firms (e.g., Dossani and Kenney 2003). However, research also finds evidence of hidden or unexpected offshoring costs and challenges that make the practice less beneficial (Dibbern et al. 2008, Larsen et al. 2013, Stringfellow et al. 2008). The geographical relocation of activities can generate major organizational changes that may not only undermine previously coherent flows of knowledge and communication, but also force additional investments into costly coordination efforts (e.g., Jensen et al. 2013, Srikanth and Puranam 2011). When activities are co-located, firms may rely on informal coordination mechanisms as daily challenges can be solved in a face-to-face manner (Allen 1977, Storper and Venables 2004). However, as activities become geographically dispersed, the opportunities for building collegial social environments and common ground due to less communication and shared context are undermined (Srikanth and Puranam 2011). For example, after offshoring parts of its activities, Nokia was forced to experiment with new configurations that could accommodate the unexpected coordination challenges between Denmark and China.

Accordingly, to address the magnified coordination costs of offshoring, we stress that firms must engage in local adaptive search to understand the technological landscapes underlying their international organizations (see, for example, Ethiraj and Levinthal 2004a, Rivkin and Siggelkow 2003). A technological landscape describes the structure and interdependencies of firms' underlying micro-activities—such as component design, product production, product assembly, and marketing—and represents the "true underlying structure of the system of interdependent choices" (Ethiraj and Levinthal 2004b, p. 162). Thus, the purpose of adaptation is to reconfigure elements in firms' organization to match the underlying technological landscape. The closer the match between the organizational configuration and the technological landscape, the better the firms' utilization of its resources and, thus, its performance (Levinthal 1997).

In this respect, successful adaptation requires knowledge about the individual organizational activities that constitute the technological landscape and how those activities can best be integrated into an organizational system. In the literature, this "architectural knowledge" (Baldwin and Clark 2000, Brusoni and Prencipe 2006, Ethiraj and Levinthal 2004a, Henderson and Clark 1990) is defined as an "understanding of how components in an organizational system are related to each other" (Puranam et al. 2012, p. 420). Henderson and Clark (1990), for example, refer to architectural knowledge as consisting of knowledge about the different components underlying a distinct system (i.e., product technology) and knowledge about how those components are integrated into an orchestrated systemic whole.

To understand the performance implications of acquiring architectural knowledge in offshoring we explore two distinct learning strategies: a *host-based learning strategy* and a *home-based learning strategy*. First, a firm can commence the adaptation process *after* the activities have physically been offshored, as in Nokia Denmark's case. In such cases, the firm commences an adaptive search for organizational configurations based on the technological landscape, but it does not do so until it encounters the actual costs of offshoring. This strategy allows the firm to avoid up-front investments in accumulating architectural knowledge during the onsite transition phase, as it only accumulates architectural knowledge through experiential learning. As firms encounter the actual challenges of

offshoring, they become better able to understand how to adapt to those challenges and, thereby, enhance performance. Along these lines, studies by Szulanski and Jensen (2006, 2008) on the international expansion of franchise projects in which exact copies of the existing template turn out, at least initially, to be the best performing strategy indicate that adaptation before internationalization is less beneficial. Therefore, this approach is supportive of research that views offshoring as a learning-by-doing process (e.g., Jensen 2009, Manning et al. 2008, Maskell et al. 2007) and, more broadly, the view of emergent strategies (Mintzberg and Waters 1985). We refer to this strategy as a *host-based learning strategy.*

Second, a firm can accumulate architectural knowledge *prior to* the actual offshoring by employing different measures to improve its understanding of how it can best adapt to the technological landscape appearing after offshoring. In other words, firms can use the disposable time before the physical relocation, while the activities are still co-located, to experiment with different adaptation possibilities. This may involve experimenting with the reconfiguration of activities in distinct but co-located units in order to understand the roles and functions of the activities to be offshored, and how those activities are interconnected. This strategy of due diligence, or "strategic planning" (Ansoff et al. 1970, Puranam et al. 2006), is in accordance with the literature suggesting that firms with explicit, corporate-wide strategies for offshoring generally experience better performance (e.g., Massini et al. 2010). Henceforth, we refer to this type of strategy as a *home-based learning strategy*.

In comparing these learning strategies, we seek a better understanding of the performance implications of the firms' adaptive efforts in offshoring. In this respect, we focus on three specific contingencies relevant to the offshoring context: the level of coordination costs, distance, and noise in the adaptive search processes. First, as firms must devise appropriate mechanisms of communication to ensure efficient coordination in an interdependent organization, we note that the costs of using different communication measures can vary considerably (Allen, 1977). Such mechanisms may range from informal, more cost-intensive people-based mechanisms to formal, more cost-effective information mechanisms. Thus, we account for the variance in the marginal costs of devising the necessary

communication and decisions among organizational members to complete work jointly or individually across or within organizational boundaries (e.g., Galbraith 1973, Thompson 1967, Zhou 2011).

Second, as we saw in the Nokia case, a key consequence of offshoring is that the distance introduced has an impact on the coordination challenges stemming from offshoring (Kumar et al. 2009, Niederman et al. 2006, Srikanth and Puranam 2011). For example, when its activities were co-located in Denmark, Nokia could rely more on informal coordination to ensure joint action. However, after offshoring, Nokia was forced to invest in new coordination mechanisms based on travel, personnel rotation, and socialization—the costs of which are largely proportional to the physical distance between the units. Employees at geographically dispersed locations may have few opportunities to engage in informal, face-to-face coordination, and they may find themselves forced to rely on less effective technology-based coordination mechanisms (Allen 1977, Cummings and Kiesler 2007, Storper and Venables 2004). Project teams may find it more difficult to build collegial social environments and common ground (Clark and Brennan 1991, Kraut et al. 1990), and may instead opt for what Siegel and Larson (2009) term "flexible intermediate adaptation" to uphold and increase performance. Therefore, while prior models of adaptation have not explicitly addressed the impact of geography, we focus on explicitly on distance and its impact on the challenges of coordination. While we acknowledge the multidimensional nature of distance (e.g., Berry, Guillen, and Zhou 2010), our focus on the geographical dimension is motivated by fact that it is likely to be a particular problematic type of distance for offshoring firms, as it is directly associated with key sources of coordination costs including travel time and cost (Asmussen and Goerzen 2013). Moreover, geographical distance can be seen as a proxy for other types of distance, since offshoring to physically distant locations often brings with it a cultural and institutional element as well (as in the Nokia case above).

Finally, as offshoring eventually implies the relocation of technologies to foreign locations, we focus on the impact of technological uncertainty and the resulting noisy performance signals it produces (e.g., Fleming 2001, Knudsen and Levinthal 2007, Lant and Mezias 1990, Levinthal 1997, Lounamaa and March 1987). Specifically, the uncertainty associated with the relocated technologies—coming from

factors such as demand fluctuations (Storper 1996) and technological changes (Teece and Pisano 1994)—creates noise that may impact the processes of adaptation in significant manner (e.g., Denrell and March 2001, Nelson and Winter 1982, Sommer and Loch 2004). In the Nokia case, the rapid evolution of technologies in the mobile-phone industry meant that the performance-related signals arising from altered configurations were obscured by noisy performance signals. In contrast, a company operating in an industry characterized by stable supply and demand, and low technological uncertainty—an example could be the cement industry—would be less exposed to noise. Notably, noise can create errors in perceiving or interpreting experience (Lounamaa and March 1987, Lant and Mezias 1990, Miner and Mezias 1996). For example, in their simulation study of firm adaption, Denrell and March (2001, p. 533) argue that "noise generates errors in the feedback on which adaptation is based and produces failures (eliminations) and successes (survivals) that are arbitrary relative to the true potentials at the time." Similarly, Lounamaa and March (1987, p. 118) emphasize that "since noise has a greater impact on performance than any single change in the control variables, the search for a good value for the coordination factor becomes a random, highly unstable, process with an outcome worse than any reasonable fixed level of coordination." Following this logic, we henceforth use the term "noise" to refer to the degree of technological uncertainty inherent in the focal relocated technology.

THE MODEL

We develop a model that allows us to simulate and investigate firm adaptation in the context of offshoring (see Online Appendix 2 for associations to similar models). In the model, the firm faces a fixed, exogenous technological landscape and chooses its configuration of activities against this landscape, assigning and reassigning various activities to different organizational units. To illustrate, after the relocation of its product-development function to China, Nokia began to experiment with the geographical composition of engineers assigned to product-development projects with the purpose of managing the coordinative challenges. We assume that the company initially has no architectural knowledge as all activities previously have been co-located and coordinated informally, but that such knowledge is necessary once it embarks on offshoring. In order to introduce and execute our model, the

following characteristics are specified: a) the underlying technological landscape; b) a function introducing the key parameters of firm performance, including coordination costs, the compounding effect of distance, and the impact of noise; c) a description of the two different offshoring learning strategies firms may employ for adaptation; and d) the contingencies for the simulation, including the value-parameters and their relationship to the offshoring context.[2]

The technological landscape

A firm's technological landscape includes information on whether its activities are interdependent and therefore need coordination. Without loss of generality, we assume 100 activities in our model. The structure of the interdependencies in the technological landscape is not completely random, as activities can often be grouped according to their natural interdependencies. For example, one can assume that the sub-activities within Nokia's product-portfolio planning (e.g., road and concept mapping) and product development (e.g., product development, manufacturing, and delivery release) activities are more tightly coupled together than the two groups of activities are interlinked with each other (the interdependency represented by P0 in Figure 1). To capture this idea, we assume that the landscape consists of two larger "natural modules" in which activities 1-50 belong to Module A and activities 51-100 belong to Module B. This structure is initially unknown to the firm's decision makers, but its performance impact can be exposed over time through experimental learning. We define the technological landscape's *degree of modularity* ($x \in [0,1]$) as the extent to which the interdependencies between activities occur within, rather than across, Modules A and B. With no modularity $(x = 0)$, activities are not only interdependent on other activities within the same module but also (and equally strongly) on activities in the other module. Hence, there is no obvious way for the firm to group its activities into two units. With full modularity $(x = 1)$, each activity is *only* interdependent on other activities within the same module, and the modules are thus attractive candidates for such a grouping. We model the extent to which a pair of activities are

[2] Please note that the full code of the simulation (in VBA) is available as an Online Appendix to this article.

interdependent on each other as a binominal outcome (0, 1), which is determined in our model by the probability $p_{ij} = xM_{ij} + \frac{1}{2}(1-x)$, where $M_{ij} = 1$ if activities *i* and *j* are in the same natural module (in other words, both are in A *or* both are in B) and 0 otherwise. Hence, the higher the *x*, the more modular is the landscape.[3] The derived technological landscape with its predefined interaction structure remains constant over time in each individual run of the model.

Modeling performance in the context of offshoring

Managers make adaptation choices regarding the structure of activities with respect to each activity's assignment to an organizational unit and, thus, its location (at home or abroad). Unlike the fixed technological landscape, adaptation efforts are endogenous to the decisions of managers. At any given time, there is no guarantee that the configuration of activities in the firm's units reflects the grouping implied by the natural modules (although the firm's coordination costs will be lower if it does). Therefore, the purpose of accumulating architectural knowledge is to understand the technological landscape in order to ensure efficient adaptation. We assume the firm is able to reassign and relocate any activity except for a subset consisting of activities 1 to E (with $0 < E < 50$), which are locked in unit 1 in the home country and cannot be offshored. Our assumption is that these E activities are locally embedded in the home country—e.g. key R&D activities that are closely linked to domestic universities, specialized skills present in the domestic labor force, or tasks central to the firm's core competencies. Furthermore, we assume this is known by the firm's managers who will therefore keep them in the home country.[4] In contrast, the rest of the activities (activities $E + 1$ to 100) can be considered 'footloose' in the sense that they can be placed freely either at home or abroad.

Based on the firm's configuration of activities into the two units at a given point in time, we model performance at that time as the result of a constant revenue stream (denoted R), from which we

[3] This is shown by the fact that setting $x = 0$ results in $p_{ij} = 1/2$, which implies that the natural modules have no impact on the random structure of interdependencies, while setting $x = 1$ results in $p_{ij} = M_{ij}$, which makes the interdependencies fall predictably into the two natural modules.

[4] We thereby rule out the risk that the firm accidentally offshores its core competencies and the potential performance consequences of doing so.

subtract the costs of production (P) and the costs of coordination (K), both of which are determined by the activity configuration. Finally, to capture noise, we add a normally distributed stochastic term (ε) with a mean of 0 and different degrees of standard deviation (σ). Performance is thus given by:

$$\pi = R - P - K + \varepsilon \quad [1]$$

Production costs are defined as $P = A_H P_H + A_F P_F$ where A_H is the number of activities currently performed at the home location and A_F at the foreign location, P_H is the production cost of one activity at home, and P_F the production cost abroad. We assume that the activities can be conducted at a lower cost abroad ($P_F < P_H$) as this is a key reason to offshore in the first place. To model coordination costs, we assume that a marginal coordination cost (k) is incurred for every activity pair that is linked by interdependencies. We assume that the cost of coordinating two activities between two units is higher than the cost of coordination within the same organizational unit, even if these two units are located in the same country. As seen with Nokia Denmark prior to offshoring, as activities within each unit may share common inputs, and as each unit may develop its own tacit knowledge, informal communication styles, formal communication channels, and value systems, coordination within a unit is easier than coordination between units. Thus, the coordination of intra-unit activities can be based on common ground and knowledge to a greater extent than the coordination of inter-unit activities, which relies more on costly ongoing communication (Srikanth and Puranam 2011). Formally, this can be expressed as $k_{LW} < k_{LB}$, where L refers to local coordination, and W and B refer to within a unit and between units, respectively. For simplicity but without loss of generality, we set $k_{LW} = 0$ in the model, but assume that $k_{LB} > 0$.

We model the compounding effect of distance on coordination by assuming that $k_{LB} < k_{IB}$, where I represents the marginal coordination costs associated with international activities, so that there is a hierarchy of coordination costs: $k_{LW} = 0 < k_{LB} < k_{IB}$. We set $k_{IB} = (1 + D)k_{LB}$ and let $D > 0$ capture the impact of geographical separation on coordination costs. Hence, D can be interpreted as the

geographic distance between the home base and the offshoring location and its impact on coordination costs, and the higher the distance, the higher a coordination cost penalty is incurred by the firm

Given these assumptions, the total cost of coordination is determined by the number of local inter-unit (N_{LB}) and international inter-unit (N_{IB}) interdependencies, where the number of activity pairs with interdependencies (*N*) is multiplied by the marginal costs of coordination (*k*) for each type of interdependency. Formally, this can be written as:

$$K = N_{LW}k_{LW} + N_{LB}k_{LB} + N_{IB}k_{IB} = \left(N_{LB} + N_{IB}\left(1+D\right)\right)k_{LB}. \quad [2]$$

Finally, our modelling of noise (with the term ε in Equation 1) is similar to prior research that seeks to understand the impact of noise or unforeseeable uncertainties on adaptive search behavior (e.g., Denrell and March 2001, Levinthal 1997, Nelson and Winter 1982, Sommer and Loch 2004). For example, in his original model, Levinthal (1997, p. 946) explores the implications of "noisy search" by including an error term in the performance function. Similarly, Denrell and March (2001) subject firms' learning trials and competitive-selection processes to random errors in order to better capture the precision of adaptation. Therefore, by including a stochastic term in the performance equation, we assume that firms face noise that is conceptually different from the uncertainty of not possessing the architectural knowledge required for successful adaptation (but related as it makes it more difficult to obtain such knowledge).

The combination of the above assumptions about the technological landscape and the performance of the firm enables us to rigorously capture a core dilemma of offshoring—the trade-off between production and coordination costs—and makes it clear why architectural knowledge is such a valuable asset in the firm's efforts to solve this dilemma. To see this, note first that the firm incurs 0 international coordination costs, but substantial production costs ($100P_H$) it does not offshore. In contrast, if it offshores all of its (100-*E*) 'footlose' activities, it incurs much lower production costs ($EP_H - (100 -$

$E)P_F$) but also higher international coordination costs ($\frac{1}{2}E(100 - E - xE)k_{LB}(1 + D)$).[5] However, if the firm has acquired knowledge about its technological landscape, it would be able to place its activities according to their modular linkages, so that one unit coincides with natural module A (activities 1-50) and another one with natural module B (51-100). The latter unit can then be offshored, resulting in intermediate levels of both coordination costs ($1{,}250(1 - x)k_{LB}(1 + D)$) and production costs ($50(P_H + P_F)$). This results in superior overall performance when there is a *balance* between centrifugal forces (in our model, the cost savings of $P_H - P_F$) and centripetal forces (the international coordination costs of $k_{LB}(1 + D)$), as captured by:

$$2/(x(50 + E) + E - 50) < (k_{LB}(1 + D))/(P_H - P_F) < 1/(25(1 - x)) \quad [3]$$

Intuitively, Inequality [3] implies that the ratio of international coordination costs to production cost savings is within an intermediate range, reflecting the rivalling importance of both of these factors to offshoring firms, as earlier emphasized and demonstrated by empirical studies (Ferreira and Prokopets 2009; Larsen et al., 2013). Modular offshoring then provides an attractive way to strike a balance between these opposing forces—but can be achieved *only if* the firm possesses sufficient architectural knowledge to identify the technological interdependencies between its activities. This reinforces the importance of understanding how firms explore and adapt to the structure of the technological landscape, and thus how they obtain architectural knowledge to begin with, a process that is the focus of our simulation.

Two learning strategies for accumulating architectural knowledge

We model the knowledge acquisition process as taking place over H discrete time periods (rounds) denoted $t \in [1, H]$, with the offshoring event itself occurring at an intermediate time period $t = T$, with $1 < T < H$. The firm's performance in a given round, as described by Equations [1] and [2], constitutes the objective function that the decision maker continuously aims to improve by incrementally adapting the configuration of the firm's activities and, thereby, accumulating learning about the technological

[5] The derivation of these cost functions and the proofs of all analytical results in this paper can be found in the Online Appendix 3.

landscape. On the basis of the two strategies portrayed earlier, we construct two learning scenarios: one in which the firm commences its search for a configuration already *before* the offshoring event at time *T* (the *home-based learning strategy*) and one in which the firm only begins its search *after* offshoring (the *host-based learning strategy*). Hence, in the home-based scenario, the firm uses rounds $t \in [1, T-1]$ prior to offshoring to learn about the technological landscape, and continues this learning process in the time period after offshoring, $t \in [T+1, H]$, building on the architectural knowledge obtained in the first period. In the host-based scenario, the firm acquires no knowledge prior to offshoring, but begins to pursue a learning-by-doing approach in the time period after offshoring, $t \in [T+1, H]$.

Initial activity split and subsequent learning algorithm. At the outset of the simulation, all of the firm's activities are included in one organizational unit located in the home country, implying that no coordination costs are incurred. However, the firm splits its activities into two equally large units either in preparation for the offshoring event at time 1 (in the home-based learning strategy) or as part of the offshoring event at time *T* (in the host-based strategy). It makes subsequent modifications to this initial activity split in an attempt to improve upon it. In terms of notation, we define unit 1 as the unit that resides (or will reside after offshoring) in the home country, and unit 2 as the unit that is placed in or moved to the foreign country.[6]

Both the initial activity split and the subsequent modifications to that split are subject to the aforementioned constraint that activities 1 to E are fixed in unit 1. Other than this constraint, we assume that the initial activity split is completely random, reflecting the firm's lack of architectural knowledge. Hence, for each activity $E+1$ to 100, we draw a lottery with a probability $(50-E)/(100-E)$ that the selected activity will be placed in unit 1. This results in an expected unit size of 50 for the two units (with

[6] A related decision is whether the foreign unit remains a wholly owned part of the parent firm, becomes a joint venture with a local partner, or is made part of an outsourcing agreement with a foreign supplier (as in the Nokia Denmark example) (Mudambi and Venzin 2009). While this decision has implications for core competencies, knowledge appropriation, and other important issues, it is beyond the scope of this study. The performance elements we model—coordination costs, production cost, and noise—are just as relevant when the two units are separated by organizational boundaries as when they are contained in the same firm.

unit 1, for example, consisting of activities 1 to E and an average of $(100-E)(50-E)/(100-E) = 50-E$ of the remaining activities $E+1$ to 100, for a total of $E+50-E=50$ activities).

After this initial activity split, we assume that the company will adapt with the goal of enhancing performance. To capture adaptation, we assume that boundedly rational decision makers in each period take one activity at random and experiment with relocating it to the other unit. This experimentation process is based on making incremental changes to a benchmark that we call the "latest performance-enhancing configuration." Those changes are kept whenever they improve performance and discarded when they do not. The latest performance-enhancing configuration is the most recent configuration that resulted in improved performance (or the initial activity split if no improvements have been found so far). Therefore, in each round, the firm takes the latest performance-enhancing configuration, randomly chooses one activity between $E+1$ and 100, moves it to the opposing unit, and observes performance. If the change results in performance that is better than the performance exhibited by the most recent performance-enhancing configuration, the new configuration is stored as the "new" latest performance-enhancing configuration (overriding the old one). Future changes are then based on this benchmark. If the change results in poorer performance, it is abandoned, and future changes are made to the "old" latest performance-enhancing configuration, which may lie several rounds in the past, especially when it is close to the optimal solution. Importantly, in this learning process, we assume that it is only possible to observe aggregate performance changes as opposed to individual components of performance. Hence, the decision maker cannot know how much of the impact on performance can be attributed to changes in the underlying fit with the landscape, or the extent to which the impact is the result of round-to-round fluctuations in the noise parameter. The decision maker therefore keeps any change that increases the sum of the two.

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

Performance of the two strategies. As depicted in Figure 2, each of the two knowledge-accumulation strategies has a distinct performance profile. A firm adopting the host-based strategy does not experiment with different organizational configurations prior to offshoring. Similar to Nokia, it adapts on a learning-

by-doing approach in which it attempts to identify the best configuration for its activities after the offshoring occurs. As a consequence, the firm does not accumulate any architectural knowledge of the dispersed set-up prior to the actual offshoring (here, $T = 200$ and $H = 500$). Performance is therefore held constant up to the point of implementation. However, when the firm commences offshoring at time *T*, it begins experimenting with different configurations with the purpose of enhancing performance. Given the added distance between the domestic and foreign activities, the costs of reconfiguration and coordination are significantly higher than they were prior to offshoring.

In contrast, in the home-based strategy, the firm experiments with the configuration of activities while all activities are still co-located domestically. The purposes of the experimentation are to gain architectural knowledge and to understand the performance effects of different configurations. As Figure 2 shows, a firm that pursues a home-based strategy finds that the costs of accumulating architectural knowledge negatively affect performance immediately prior to offshoring. However, as the firm accumulates knowledge about how to best configure itself prior to offshoring, its performance improves. Moreover, as the firm has utilized the period prior to offshoring to identify a configuration that reduces coordination costs, the coordination cost increase associated with actually relocating activities abroad at time *T* are relatively low. Therefore, the firm's relocation of activities abroad has few major, disruptive implications for performance. The fact that the firm gains architectural knowledge while the activities are still co-located subsequently reduces the coordination costs associated with offshoring.

As is evident in Figure 2, the differences in performance between the two approaches create a potential dilemma. When the additional coordination costs associated with unprepared offshoring (the area between the two curves furthest to the right) are higher than the costs of accumulating architectural knowledge prior to offshoring (the area between the two curves furthest to the left), the home-based approach results in higher accumulated performance than the host-based approach. Conversely, when the opposite is the case, the host-based strategy results in higher accumulated performance. Thus, to explore this tension and derive the implications of adaptation in offshoring, we run our simulation model for a variety of parameter-value combinations.

Contingencies for offshoring: a simulation of the two learning strategies

Parameter Configuration. To set the numerical values of the parameters for the simulation, we rely on a combination of (1) a detailed analysis of the economic logic of the model, (2) quantitative data relating to the variables in our model, (3) conversations with managers from multinational firms, and (4) prior studies in the offshoring and simulation literatures. Furthermore, we subsequently provide a number of robustness tests where we deviate from our baseline parameter choices in order to test the impact of our choices on the results of the model.

First, it is important that our parameters are internally consistent with each other and with the empirical phenomenon that the model aims to explain. Our study is motivated by the observation that firms struggle to reap performance benefits from offshoring, and that a key reason for this is the apparent cost savings being hollowed out by increases in coordination costs when activities become geographically dispersed. This tension implies that a relevant model of offshoring should be calibrated so that there is balance between production cost savings and international coordination costs, implying parameter choices that fulfill Inequality [3] developed above. The alternative is to assume that centripetal and centrifugal forces are 'unbalanced', with international coordination costs that are either prohibitively high (in which case firms would never find it attractive to offshore in the first place) or trivially low (in which case firms would easily redeploy entire value chains to foreign countries) compared to cost savings. Arguably, both of these scenarios are at odds with real-world observation (e.g. Ferreira and Prokopets 2009, Larsen et al. 2013).

We can also see from Inequality [3] that the range in which these forces are balanced is determined by the number of home country embedded activities (E) and the degree of natural modularity in the technological landscape (x). In fact, a condition for this range to exist is that both of these parameters are sufficiently high, as defined by $x > (100 - E)/(100 + E)$. Intuitively, when the technological landscape is highly modular (and the entire value chain is not footloose) it is particularly useful for the offshoring firm to acquire architectural knowledge so that it can selectively relocate activities along these modular boundaries. For example, Nokia decided to only relocate a subset of their

product development processes, reflecting the more general tendency of firms to offshore carefully delimited parts of their value chains (Contractor et al. 2010). Different combinations of x and R could fulfill this constraint, but we choose in our main analysis to keep home country embeddedness relatively low ($E = 10$) and landscape modularity correspondingly high ($x = 0.9$) in order to give the firm significant room for experimentation and architectural knowledge accumulation. With these values, the condition for centrifugal and centripetal forces to be balanced reduces to $\frac{1}{7} < (k_{LB}(1 + D))/(P_H - P_F) < \frac{2}{5}$.

Based on statistics on wage differences across developed and emerging markets, we set the production cost savings at 70% (by setting $P_H = 1$ and $P_F = 0.3$) in our main run of the simulation.[7] This choice, in turn, implies a parameter range for the international coordination costs where $0.10 < k_{LB}(1 + D) < 0.28$. Again, many different combinations of k_{LB} and D could fulfill this constraint. However, our conversations with executives from the telecommunications sector have indicated that coordination costs might be roughly 3 to 4 times as high after offshoring as they are before, depending on the distance.[8] The sources of these additional costs include the increased time that individuals spend on coordination activities, the need to create dedicated liaison positions that specialize in coordination across functions and borders, the costs of business travel relating to coordination meetings, and a need for socialization by rotating people across borders to understand local context and share tacit knowledge. These mechanisms are to a large extent driven by the loss of face-to-face interaction resulting from geographic separation of activities (Storper and Venables 2004).

Hence, to capture a tripling or quadrupling of coordination costs, we set $D = (2, 3)$ in our model, and combine those values with $k_{LB} = (0.04,\ 0.06)$ in order to arrive at a reasonable range for $k_{LB}(1 + D)$, which then varies from 0.12 to 0.24. This is well within the required range for international

[7] The wage statistics are found in "Prices and Earnings", CIO Wealth Management Research, UBS, September 2012. We took the average ratio of engineering wages in selected emerging market cities (Rio de Janeiro, Taipei, Sao Paolo, Tallinn, Budapest, Bratislava, Prague, Shanghai, Mumbai) to engineering wages in selected developed market cities (Copenhagen, Munich, Tokyo, and Chicago) and rounded it up to 0.3.

[8] A summary of an interview with a TelCo executive, and calculations of different coordination cost scenarios based on this interview, is available from the authors upon request.

coordination costs calculated above (0.10 to 0.28) while still giving us enough variation in these costs to assess the importance of the underlying parameters. The average ($k_{LB} = 0.18$) results in the selective offshoring strategy incurring expected international coordination costs of $1{,}250(1-x)k_{LB}(1+D) = 22\frac{1}{2}$, which is about 64% of the expected production costs savings of 35. This is consistent with estimates from offshoring consultants implying that slightly more than half of the wage cost savings are often offset by the 'soft costs' of offshoring (neoIT, 2004).

In addition to these choices, we also need specific values for noise, timing, and revenue in order to run the simulation. As noted by Levinthal (1997, p. 947), "it is appropriate to calibrate [the noise parameter] ϵ relative to the magnitude of the distribution of actual fitness values." We adopt this principle in our simulation to avoid the risk of setting noise levels that are out of proportion to the underlying fitness levels. Arguably, the appropriate calibration benchmark in the context of our specific model is the *coordination cost change* that provides feedback in the learning process, since our noise parameter is conceptualized as a disturbance that interferes strongly or weakly with the acquisition of architectural knowledge. To see the impact of noise clearly, we therefore suggest that 'low' noise should mostly enable learning even while allowing for occasional mistakes, whereas 'high' noise should reduce learning about the landscape to a minimum, but without eliminating it altogether. We operationalize this as having a 95% probability of keeping a good decision when noise is low and 55% when it is high[9]. It can be shown that probabilities of this magnitude are achieved in the first round of the simulation when setting low noise to $\sigma = 0.15$ and high noise to $\sigma = 2$ (underlying calculations can be found in Online Appendix 3).

We set the horizon of the model to $H = 500$ and the time of the offshoring event to $T = 200$, as these choices seem to give sufficient time to exploit (without fully exhausting) learning opportunities both before and after offshoring. Finally, we set $R = 1{,}000$. This is without loss of generality since, being

[9] 50% is a natural lower limit for this probability, since that implies that the decision maker does not see any difference between the good or bad changes and therefore applies the same stochastic decision rule to them. Probabilities below 50% would imply that the decision maker is biased *against* good changes, which defies both common sense and the logic of our model.

constant across the two strategies, the revenue disappears when we difference them and thus has no effect on our conclusions.

RESULTS

The results of our simulation are reported in Table 1. Since the technological landscape is randomly drawn, the reported results are averaged over 100 landscapes to smooth out the stochastic component in any single landscape (for similar procedures, see e.g. Ethiraj and Levinthal, 2004a, 2004b, Ethiraj et al. 2008). To derive each cell in the table, we set the specified values of k_{LB}, σ, and D for that cell. Based on those parameter values, we run 50 simulations of the host-based strategy and 50 simulations of the home-based strategy on each of the 100 landscapes, for a total of 5,000 simulations of each strategy for each cell. To determine the relative attractiveness of the two strategies, we compare the total accumulated performance of each strategy over the 500 time periods ($\sum_{t=1}^{500} \pi_t$). We average the cumulative performance of each strategy over those 5,000 simulations and subtract the cumulative performance of the home-based strategy from that of the host-based strategy. The resulting number is reported in the relevant cell, with a positive number indicating that the host-based strategy yields higher performance than the home-based strategy and a negative number indicating the opposite.

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

In Table 2, we treat each landscape of our simulation as a random sampling from a "population" of landscapes and apply statistical techniques to the averages of those 100 landscapes. This enables us to assess whether the effects of the different parameters are significant, as opposed to being merely caused by fluctuations from landscape to landscape. Specifically we take the differences between the averages in Table 1 for different parameter values and using the *t*-test to assess whether those differences are high enough to warrant a firm conclusion given the underlying standard deviation. In the following, we discuss the implications of this table for the comparative statics of noise, distance, and coordination costs, and use these to develop a number of theoretical propositions.

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

The effect of noise

Our results strongly indicate that high noise in the performance function (measured by its standard deviation σ) makes the host-based learning strategy relatively more attractive. As mentioned above, we can see that each high-noise column in Table 1 features larger values than the corresponding low-noise column. In Table 2, this translates into positive numbers (indicating a positive effect on the relative attractiveness of the host-based learning strategy) for noise under all four combinations of the other parameters. Therefore, in situations with high levels of noise, our model suggests that firms benefit from choosing a host-based learning strategy in which successful adaptation is the result of learning-by-doing over longer periods of time. This effect is formalized as follows:

Proposition 1*: Noise has a positive effect on the relative attractiveness of the host-based strategy.*

To get a clearer indication of the mechanism underlying Proposition 1, it is useful to take a detailed look at how noise influences the performance profiles of the two strategies. As illustrated in the left panel of Figure 3, in the absence of noise, a firm pursuing a home-based strategy for offshoring incrementally learns and accumulates knowledge about how to configure the organization to enhance performance. In this example, this learning strategy is valuable because the distance to the host country is relatively large, and because a firm that decides to follow a host-based strategy of offshoring without first trying to learn about the natural modules in the technological landscape will suffer very high costs of coordination immediately after offshoring. As a consequence, as the left panel of Figure 3 shows, the home-based strategy is clearly better—the benefit of home-based learning (the area between the curves after offshoring) is greater than the costs of such learning (the area between the curves before offshoring).

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

However, as demonstrated in the right panel, this conclusion may change as soon as we incorporate noise into the model. As that panel indicates, given a high degree of noise in the performance function, the learning that would otherwise take place in the home-based strategy is less likely to occur. Therefore, the firm's performance does not improve as much prior to offshoring despite the proactive search for new configurations that will yield higher performance. As noise creates uncertainty that overwhelms the relative low coordination costs at home, the decision maker cannot properly evaluate the

effects of organizational decisions prior to offshoring. In such situations, decision makers may find that organizational configurations and preparation measures taken *prior* to offshoring in a home-based strategy may prove inadequate, and that they need to unlearn the knowledge accumulated at home while accommodating the higher coordination costs of operating in the offshoring locations. As the firm commences offshoring (t = 200), therefore, it will experience a decline in performance that is almost as large as the decline experienced by the host-based learning firm. This means that when the noise level is high, the costs of home-based learning are higher and the benefits are lower, which in turn means that the host-based strategy offers better performance. Essentially, it is not worthwhile to prepare for an event if the causality of that event can only be understood through actual experiential learning.

The effect of distance

The negative values for distance in Table 2 indicate that, in general, distance favors the home-based strategy. This is also visible in Table 1 where the high-distance row consistently contains lower numbers than the low-distance row does. Intuitively, high distance leads to a high performance penalty for the host-based learning strategy, which results in high coordination costs immediately after offshoring. In contrast, a firm adopting a home-based learning strategy has learned about the landscape in advance and, therefore, does not suffer these high coordination costs. Hence, when a firm decides to offshore activities to a location where the impact of distance on coordination costs is high, a home-based strategy may yield higher accumulated performance than a host-based strategy. Conversely, the host-based learning strategy may in fact be better when the offshoring location is more proximate, as seen by the positive numbers in the low-distance row in Table 1.

However, there is an important caveat to this conclusion: the effect of distance is not equally strong across different levels of noise. In fact, distance becomes much less important when noise is high, as indicated by the relatively weak effects and low t-values in the third and fourth row in Table 2, and in one case the effect even disappears (as the t-value becomes insignificant). As the positive effect of distance on the relative attractiveness of the home-based strategy is contingent on successful home-based learning, high noise reduces this effect. In other words, when noise is high, distance has an almost equally

strong negative effect on the home-based and the host-based strategies, whereas distance has a much stronger negative effect on the host-based strategy when noise is low. This is clear in Table 2, where both interaction terms are significant (their positive sign is due to the host-based strategy being the benchmark in the table). On this basis, we derive our second proposition:

> ***Proposition 2****: Noise negatively moderates the positive effect of distance on the relative attractiveness of the home-based strategy, such that this effect becomes weak and may disappear at high levels of noise.*

The effect of coordination costs

Finally, the magnitude of coordination costs also has implications for the relative attractiveness of the two strategies. However, the implications are even more ambiguous than for the other two parameters: high coordination costs sometimes favor the host-based strategy (especially when noise is high), while at other times it has no effect or even favors the home-based strategy (when noise is low). This surprising finding can be explained intuitively by looking at the way in which noise influences the effectiveness of home-based learning. We know that with high levels of noise, the home-based strategy does not produce much learning prior to offshoring. Therefore, the firm does not reap much of a post-offshoring benefit compared to the host-based strategy. In this case, higher marginal coordination costs merely lead to the home-based strategy incurring higher initial coordination costs without the associated benefits, which speaks in favor of the host-based strategy.

With low noise, we know that home-based learning can be effective. In that case, there are two effects of increased marginal coordination costs: an increase in the costs of home-based learning before offshoring (favoring the host-based strategy), and an increase in the benefit of learning after offshoring (favoring the home-based strategy). The latter could conceivably dominate the former. In that scenario, an increase in coordination costs is particularly costly for the host-based strategy, which experiences the full coordination costs, inflated by distance, after offshoring. For example, successful coordination in a firm may depend on costly face-to-face coordination (in contrast to formalized coordination mechanisms, such as standardization and centralization), such that employees need to be physically co-located to ensure effective joint work (e.g., research and development). This may be the case in industries that rely on tacit

and complex knowledge—types of knowledge that are difficult and costly to communicate. In these cases, our model suggests that it is beneficial to search for an organizational configuration while the activities are still co-located so that activities requiring costly coordination are placed in one country rather than across countries. The idea that noise moderates the effect of coordination costs, which is supported by the significant t-values in Table 2, is captured by our final proposition:

> ***Proposition 3****: Noise positively moderates the effect of coordination costs on the relative attractiveness of the host-based strategy, which may then be negative at low levels of noise and positive at high levels of noise.*

Robustness

In addition to the parameter configurations described above, we also performed a number of robustness tests to see to what extent the results were sensitive to changes in the other assumptions of the model. First, we examined the impact of changing the timing of the model. Hence, holding the underlying technological landscape constant, we set $T = 200$ (as above), $T = 150$ (early offshoring), and $T = 250$ (late offshoring), respectively, running 50 simulations of both strategies in each case. We then looked at how the parameter effects (as reported in Table 2) changed as a consequence of this variation. The conclusion was that the effects were virtually unchanged, with correlations between the effect size vectors for different values of *T* being in the 0.94-0.96 range. We repeated this procedure for the time horizon, setting $H = (450, 500, 550)$, with identical conclusions (correlations also in the 0.94-0.96 range). Furthermore, since we held production cost savings constant in our main parameterization of the model, we tested the sensitivity of the results to these costs in a similar manner and with similar results, setting $P_F = (0.22, 0.30, 0.38)$ and obtaining correlations in the 0.94-0.98 range.

Finally, a different take on the robustness of our results is to assess the statistical properties associated with the number of landscapes (100) we have drawn in the simulation. While more landscapes would always be better, and provide an even stronger indication that our results are not artefacts of the randomly drawn landscapes, we can at least assess the statistical confidence and power associated with 100 draws. First, as to confidence, we can see from Table 2 that all of our propositions are based on coefficients that are significant at $p<0.0001$, suggesting that 100 draws in our case is more than sufficient

to reduce the risk of type 2 error to a generally accepted level. Second, power is less of a problem since there is only one effect in Table 2 which is insignificant (the effect of distance under high noise and high uncertainty). It has an effect size (mean divided by standard deviation) of 0.07, and to detect such a low effect size with, for example, 99% confidence and 80% power, would require a sample size of 2,048 landscapes. Hence, while we cannot rule out that there we have made a type 1 error in rejecting this effect, it is worth noting the (more than 20-fold) increase in the number of landscapes that would be required to detect such a small effect, and also the fact that this effect is in any case about 1% of the effect sizes underlying proposition 1 (noise).

DISCUSSION AND CONCLUSION

In this article, we have a developed and explored a formal model of local adaptive search in the context of relocating organizational activities to foreign locations (i.e. offshoring). Our results are two-fold. First, we portray the process of organizational adaptation in the context of offshoring. We do so by juxtaposing two knowledge-accumulation strategies: *a home-based learning strategy* in which the firm starts to experiment and search for a configuration prior to offshoring while the activities are still co-located at home; and *a host-based learning strategy* in which the firm starts to search for a configuration using its experiences with the actual offshoring. We show that a firm pursuing a home-based strategy experiences comparatively poorer performance while the activities are still co-located, and that performance improves as the firm identifies configurations that reduce coordination costs. Conversely, a firm pursuing the host-based strategy experiences a significant decline in performance following the offshoring implementation, as coordination costs rise due to the spatial separation, after which it experiments with different configurations in order to improve performance.

Second, we demonstrate how the general adaptation patterns are largely dependent on the levels of geographic distance, noise, and coordination costs When firms aim to offshore to geographically distant locations, pursuing a home-based learning strategy becomes relatively more attractive, because it reduces the risk of being overwhelmed by coordination costs after the offshoring implementation. Hence, a combination of high coordination costs and high distance to an offshoring destination is a particularly

deadly combination for firms that have not done careful and elaborate preparation before offshoring. More interesting, however, we also find that when the level of noise in firms' performance function is high, the host-based learning strategy becomes relatively more attractive irrespective of the level of the other contingencies. As noise generates uncertainty, the ability to evaluate the appropriateness of the architectural knowledge is undermined and the likelihood of making inefficient design decisions increases. Noise lowers the benefits of learning at home and leaves the firm more vulnerable to higher coordination costs when it goes abroad. Thus, in situations with high levels of uncertainty, firms benefit from pursuing host-based learning strategies despite vast distances and costly coordination requirements. Noise increases the risk of judgment error (Lampel and Shapira 2001) or due-diligence failure (Puranam et al. 2006) to the point that the firm would benefit more from relying on actual experience or learning-by-doing. In that sense, Nokia Denmark's host-based approach to the offshoring of complex product-development activities may have been a sound one, even though it led to unexpected costs and problems that required corrective action. Given the noise that arguably exists in the highly volatile mobile-phone industry, it may have been very difficult for Nokia Denmark to accumulate the necessary architectural knowledge through a home-based strategy. Moreover, an attempt to do so might have created a risk of accumulating the wrong knowledge about the underlying technological landscape, which may have led to a need to unlearn knowledge as the organization embarked on offshoring.

With this study, we contribute to research on offshoring and the global distribution of work (Contractor et al. 2010, Jensen et al. 2013, Srikanth and Puranam 2011). In our formal modeling of how firms adapt to underlying international technological landscapes, we have investigated two distinct offshoring strategies that yield different performance implications given central contingencies—marginal coordination costs, the impact of distance on the coordination of international activities, and the role of noise in the performance function. Arguably, adaption in an international context includes both a spatial and an organizational dimension, where the former involves adaption to the differences manifested in the host locations and the latter relates to making the value chain work in a new setting (Szulanski and Jensen 2008). However, while most international business research has focused on how firms adapt along the

spatial dimension (e.g., Lord and Ranft 2000, Makino and Delios 1996, Siegel and Larson 2009), this study stresses the performance implications of the ways in which firms gain architectural knowledge when going abroad. In particular, we argue that the added distance between organizational activities increases firms' coordination costs and that they must search for new configurations that fit the international dispersion in order to optimize performance. As such, firms must accumulate both local-market knowledge and architectural knowledge (Baldwin and Clark 2000, Brusoni and Prencipe 2006, Ethiraj and Levinthal 2004a, Henderson and Clark 1990). In fact, one of the advantages of our model is that we conceptualize and formalize architectural knowledge as distinct from local market knowledge, in contrast to most studies on international expansion, which lump these two types of knowledge together. Future research could, therefore, carefully investigate how distance affects the interdependencies among organizational units when reconfiguring and how those interdependencies eventually affect performance (see also Kumar et al. 2009, Srikanth and Puranam 2011). Relatedly, future research could empirically investigate how decision makers accumulate architectural knowledge in the process of offshoring.

Moreover, our study suggests that the accumulation of architectural knowledge (Ethiraj and Levinthal 2004a, Henderson and Clark 1990) presents firms with a strategy that is useful to balance the tradeoffs among strategic rationales—such as lower production costs in foreign locations with the costs of coordination and distance. However, our results suggest that the noise surrounding such decisions is particularly detrimental in shaping effective adaptation processes. Accordingly, we argue that noise can lead to situations of causal ambiguity in which firms cannot determine the causes of their performance (Lippman and Rumelt 1982, Powell et al. 2006). In such situations, firms and their decision makers are unable either ex ante or ex post to produce an unambiguous explanation of how the key components of a system work and interact (Denrell and March 2001, King and Zeithaml 2001). While it has been argued that firms must rely on additional heuristics to guide effective adaptation in noisy situations (Lounamaa and March 1987, Denrell and March 2001), we find that noise, in general, undermines firms' abilities to accumulate the architectural knowledge necessary for adaptation. Therefore, efforts to learn prior to implementation may be counterproductive or based on incorrect premises.

Rather, firms that are able to recognize noisy situations will experience more accurate search and better outcomes. Instead of being stuck on a suboptimal peak as a result of an imprecise home-based search strategy, firms that acknowledge the need for more accurate performance signals would sustain a comparative advantage. In our context, such performance signals would be more easily attained through a host-based search strategy. Accordingly, we suggest that it is important to consider the ability of firms to identify noisy situations and thus the need to explore more distant search options when planning on how to most efficiently accumulate architectural knowledge (see also Knudsen and Levinthal 2007, Gavetti and Levinthal 2000). Importantly, we hold that future research should pay much closer attention to the concept, antecedents, and consequences of noisy search in processes of international expansion and learning. For example, under what contingencies are search processes likely to be noisier? How can noise be captured empirically? Is noisy search unavoidable? Can some firms better foresee and cope with the challenges of noise? Undoubtedly, unraveling the answers to such questions would be of vast importance in advancing our understanding of firms' adaptation processes. Hence, while noise is an exogenous parameter in our model, a possible extension could be to endogenize it, for example modeling it as a function of industry or market characteristics or of the actions and strategies pursued by the firm. Also, as opposed to our (technology-driven) noise function, other types of noise could be explored, such as those stemming from the value chain activities' geographic footprint or their distribution across firm boundaries (e.g. outsourcing) (see e.g. Levy 1995).

Taken together, our results shed light on the conventional wisdom on the initiation of learning processes in offshoring (e.g., Massini et al. 2010), and on the value of strategic planning and due diligence in general (Ansoff et al. 1970, Puranam et al. 2006). We demonstrate that the firms' strategies are subject to learning, and that learning depends on the signal-to-noise ratio. Thus, rather than confirming the proposition that firms that prepare upfront by implementing predefined, corporate-wide offshoring strategies are more likely to generate higher offshoring performance, our results suggest that firms may benefit from pursuing a learning-by-doing strategy in some cases, especially when the noise levels inherent in the technological landscape are high. With higher noise, the performance signals are

weak, making it difficult for firms to accumulate proper architectural knowledge through a home-based strategy. In this situation, a firm might run the risk of accumulating the wrong knowledge about the underlying technological landscape, which would result in a need to unlearn knowledge as it embarks on offshoring. While we examined this paradox in a simulation study of offshoring, future research could investigate other organizational and environmental contingencies that may be equally relevant for firms attempting to address this paradox. For example, although our model is designed with the primary purpose of understanding adaptation in offshoring, its underlying logic of architectural knowledge accumulation given organizational reconfigurations is applicable to other contexts, such as diversification (Rawley 2010), unit reconfigurations (Karim and Williams 2012), and, as mentioned above, outsourcing (Williamson 2008). As to the latter, our arguments are general enough to apply to all scenarios in which coordination costs are inflated by distance, and such scenarios would arguably also include outsourcing, given that coordination with third parties located in distant countries is more difficult than coordination with domestic outsourcing partners. Nevertheless, an extension of our model could be to model both offshoring and outsourcing choices explicitly, as the two dimensions could have potentially compounding implications for coordination and production costs.

Our findings are largely in line with the work of Szulanski and Jensen (2006, 2008), who also focus on the role of architectural knowledge accumulation. Their studies on franchising projects focus on the temporal aspects of adaptation after going international. They find that, initially, architectural knowledge is key, while local market adaptation only becomes important at a later point. We go beyond such studies by including the pre-offshoring phase and the possibility of a home-based learning strategy aimed at predicting the configurations that might work after offshoring. Similar to Szulanski and Jensen (2006, 2008), we find that home-based learning cannot serve as a substitute for experiential learning after offshoring in some cases.

In this respect, however, it should be mentioned that we have examined two rather stylized strategies of offshoring—i.e., home- and host-based learning. Naturally, other firms may opt for other strategies. For example, a firm may decide to have an entire team spend some months together doing pilot

tests of reconfiguration either at home or at the host location. Pursuing this strategy would enable the teams to establish mechanism of tacit coordination, being defined as "mechanisms that enable the formation and leverage of common ground without the need for direct, ongoing communication" (Srikanth and Puranam 2011, p. 850). Thus, by establishing common knowledge and shared focal points through socialization efforts teams can create a basis of shared knowledge that enables interacting agents to accurately adjust and align their actions to each other—in other words, to coordinate successfully. Thus, going forward, we encourage future research to investigate the costs and benefits of such strategies in processes of adaptation when offshoring.

Finally, we contribute to research that embraces formal methods to investigate firm adaptation by acknowledging that distance, noise, and different strategies for accumulating architectural knowledge affect firm performance. While some models have focused on noise or uncertainty in an attempt to understand adaptive search (e.g., Denrell and March 2001, Levinthal 1997, Knudsen and Levinthal 2007, Sommer and Loch 2004), the impact of geography and distance has largely been neglected. In our model, we show how noise and the distance between organizational units magnify coordination costs and, consequently, complicate the process of adaptation. As such, we demonstrate how distance shapes the structure of firms' underlying performance landscapes. Moreover, our model is unique in terms of its simulation of local search strategies given the implementation of a strategic initiative (i.e., the inclusion of foreign operations). This approach has allowed us to investigate a central question regarding the effects and value of different learning strategies. Indeed, opposing search strategies, such as cognition versus experiential search (Gavetti and Levinthal 2000), search versus stability (Rivkin and Siggelkow 2003), and integrated versus chunky search (Baumann and Siggelkow 2014), are emphasized in the modelling literature. However, by including an exogenous shock to the model, we have been able to isolate and compare the opposing learning effects in the context of strategy implementation. Future research on strategy implementation processes could therefore apply approaches similar to the one presented here.

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Figure 1: Nokia product development

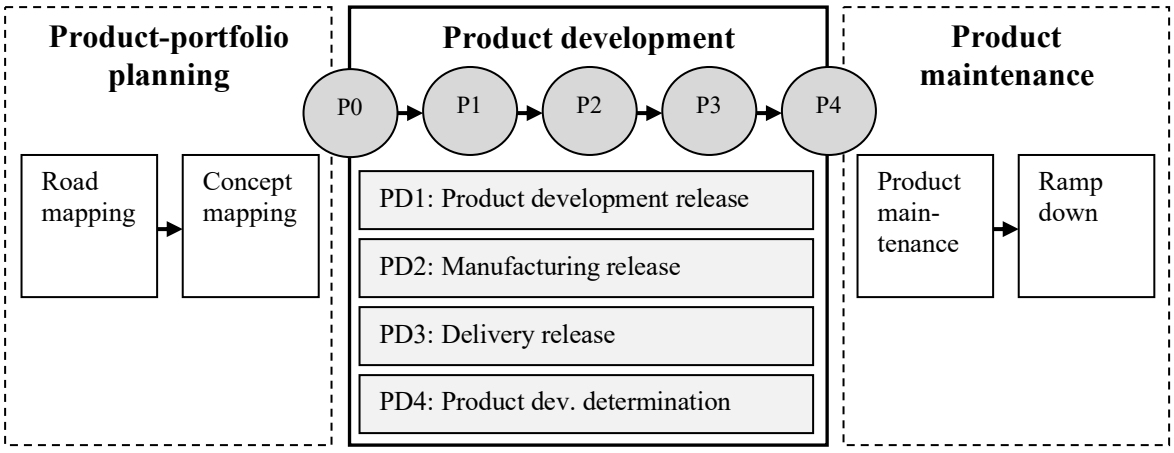


Figure 2: Performance profiles of the two strategies

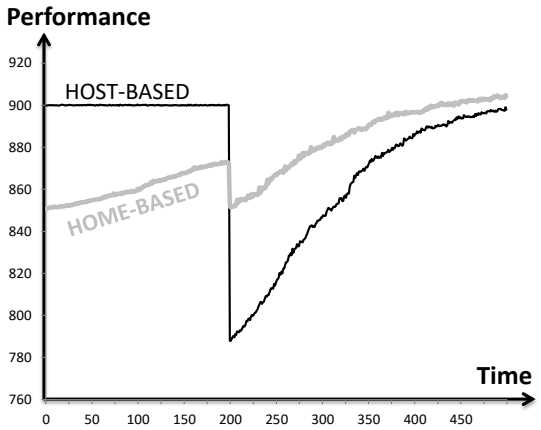
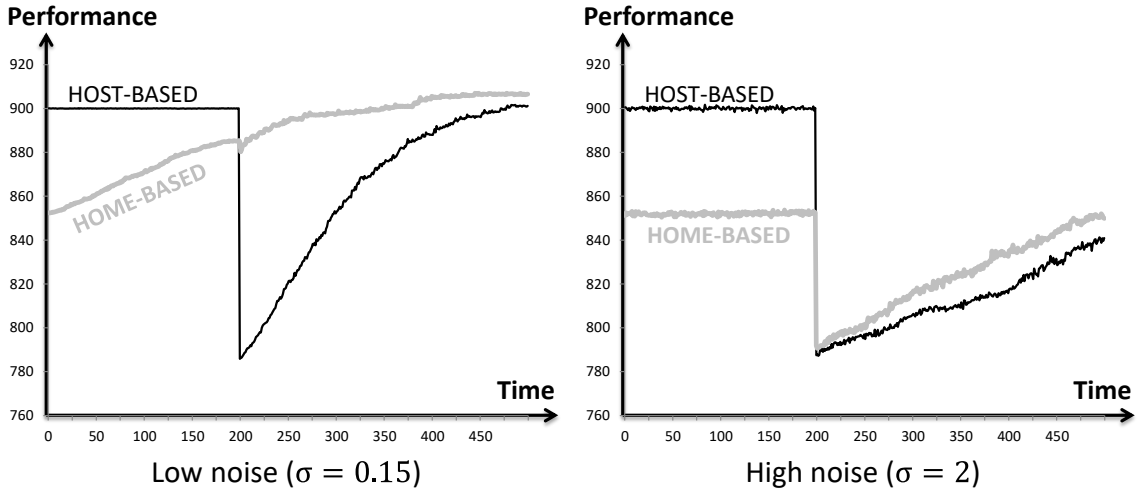


Figure 3: Impact of noise on the two strategies



Low noise ($\sigma = 0.15$) High noise ($\sigma = 2$)

Table 1: Relative attractiveness of the host-based strategy

	Low coordination cost ($k_{LB} = 0.04$)		High coordination cost ($k_{LB} = 0.06$)	
	Low noise ($\sigma = 0.15$)	High noise ($\sigma = 2$)	Low noise ($\sigma = 0.15$)	High noise ($\sigma = 2$)
High distance ($D = 3$)	-9,476	8,246	-15,647	11,192
Low distance ($D = 2$)	-4,687	9,183	-9,414	11,489

Table 2: Effect of parameters on relative attractiveness of the host-based strategy

Effect of	**Contingencies**	**Avg.**	**SD**	**N**	**T**
Noise	Low distance, low c. cost	13,870	1,475	100	93.9**
Noise	Low distance, high c. cost	20,903	3,034	100	68.9**
Noise	High distance, low c. cost	17,722	2,124	100	83.5**
Noise	High distance, high c. cost	26,839	3,344	100	80.3**
Distance	Low noise, low c. cost	-4,789	919	100	-52.1**
Distance	Low noise, high c. cost	-6,233	1,566	100	-39.8**
Distance	High noise, low c. cost	-937	2,485	100	-3.8**
Distance	High noise, high c. cost	-296	4,044	100	-0.7
C. cost	Low distance, low noise	-4,727	1,038	100	-45.5**
C. cost	Low distance, high noise	2,306	3,237	100	7.1**
C. cost	High distance, low noise	-6,171	1,493	100	-41.3**
C. cost	High distance, high noise	2,946	3,361	100	8.8**
Noise * distance	Low c. cost	3,852	2,639	100	14.6**
Noise * distance	High c. cost	5,937	4,495	100	13.2**
Noise * c. cost	Low distance	7,033	3,521	100	20.0**
Noise * c. cost	High distance	9,117	3,753	100	24.4**

"c. cost" = coordination cost, * p<0.001, ** p<0.0001.