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The Impact of Complexity on Knowledge Transfer in Manufacturing Networks

Markus Lang, Patricia Deflorin, Helmut Dietl, Eric Lucas
Department of Business Administration, University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland, markus.lang@business.uzh.ch, patricia.deflorin@business.uzh.ch, helmut.dietl@business.uzh.ch, eric.lucas@business.uzh.ch

Coordinating knowledge transfer within multi-plant manufacturing networks is a challenging task. Using a computational model, we examine when it is beneficial to create production knowledge within a central unit, the "lead factory," and transfer it to geographically dispersed plants. We demonstrate that the knowledge transfer generates a trade-off between a positive cost-saving effect due to fewer adaptations in each plant, and a negative transfer cost effect due to the costly knowledge transfer itself. The complexity of the production process moderates the performance implications of the knowledge transfer because it determines the relative strength of these two effects. For production processes with low complexity, knowledge transfer can engender superior network performance. Here, an optimal extent of knowledge transfer exists, and thus, a complete knowledge transfer is not performance maximizing. For production processes with medium and high levels of complexity, performance is reduced rather than enhanced through knowledge transfer so that it is optimal not to transfer any knowledge from the lead factory to the plants. While we analyze knowledge transfer within a manufacturing network, our results are transferable to other settings that consist of a knowledge sending and receiving unit.

Key words: manufacturing network; knowledge transfer; lead factory; complexity; NK model
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1. Introduction

Many companies organize their manufacturing activities as a distributed network of multiple production plants. The coordination of such networks is a challenging task. A key management issue is the transfer of production knowledge within such a network. Production knowledge is a recipe for action and provides guidance for how to produce a good (Ferdows 2006). It can be built up within each plant or it can be transferred from a central unit: The so-called lead factory (Ferdows 1997). The lead factory acts as an intermediary between R&D and the geographically dispersed plants and translates R&D knowledge into production knowledge (Simon et al. 2008).

Within manufacturing networks, there is a fundamental trade-off between transferring production knowledge to the plants and letting the plants create their own knowledge. In our study, we formally explore this trade-off by analyzing the performance implications of the knowledge transfer within a multi-plant manufacturing network with a lead factory and geographically dispersed production plants.

Knowledge resides in members, tools, and tasks (Argote and Ingram 2000). It can be explicit (as in production manuals) or tacit (stored in the heads and hands of the employees) (Teece 1977). Depending on the type of knowledge, its transfer can be costly. Explicit knowledge can be transferred with manuals and through systems. However, a codified recipe cannot capture all the subtle nuances of a process. It is contingent on operating conditions and scale and often tacit in nature (Hayes et al. 2005). Conveying tacit production knowledge often requires moving of people (Argote 1999). Considering the distributed network of plants, moving experts to each plant can be costly. However, not transferring the knowledge to save the costs results in other costs because each plant would have to create its own production knowledge. The search for optimal process sequences, machine adjustments, raw material usability, and other production-related decisions is time consuming and leads to adaptation costs (Lapré et al. 2000). Each global plant manager therefore has to decide whether it is more advantageous to create production knowledge within a lead factory and to transfer it to the geographically dispersed plants or to let each plant create its own production knowledge. However, as locally acquired knowledge is difficult to disseminate (Lapré et al. 2000), we need to understand which conditions make knowledge transfer more or less beneficial.

Our study assesses the performance effects of knowledge transfer within a multi-plant manufacturing network and discusses the implications for network configuration. In particular, we are interested in how the complexity of the production process and the heterogeneity among production plants moderate the effect of knowledge transfer on performance. For our

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analysis, we construct an NK performance landscape model and extend the standard formulation (e.g., Levinthal 1997, Rivkin 2001) by adding the following features: (a) We assume that knowledge can be transferred from a lead factory to the production plants. Thus, the plants can benefit from the production knowledge generated in a lead factory in the sense that a subset of production decisions (extent of knowledge transfer) matches the production setting of the lead factory. A global plant manager can control the extent of knowledge transfer. (b) Knowledge transfer is costly and results in one-time transfer costs for each plant. (c) Each actual implementation (but not evaluation) of a new production setting in a plant is associated with adaptation costs.

Our simple model shows that the knowledge transfer generates a trade-off between a positive cost-saving effect due to fewer adaptations in each plant, and a negative transfer cost effect due to the costly knowledge transfer itself. The complexity of the production process and the plant heterogeneity have an impact on the relative strength of these two effects, and thus, they determine how beneficial knowledge transfer from the lead factory to the plants is. For production processes with low complexity, knowledge transfer can engender superior network performance. Here, an optimal extent of knowledge transfer exists, and thus, a complete knowledge transfer is not performance maximizing. For production processes with medium and high levels of complexity, in contrast, performance is reduced, rather than enhanced, through knowledge transfer so that it is optimal not to transfer any knowledge from the lead factory to the plants. As the heterogeneity between the lead factory and the plants increases, the positive effect of knowledge transfer decreases. While the usefulness of the lead factory's production knowledge linearly decreases as plant heterogeneity increases, it non-linearly decreases as the complexity of the production process increases. Our results not only provide implications for manufacturing network coordination, but also may enhance our understanding of organizational learning and adaptation.

A number of studies analyze the processes through which knowledge is transferred, and the factors affecting this transfer (Bartlett and Ghoshal 1989, Ferdows 2006, Gupta and Govindarajan 2000, Szulanski 1996, Tsai 2001). For example, Zander and Kogut (1995) and Szulanski (1996) analyze the properties of knowledge and show that knowledge that is not well understood or is high in causal ambiguity is harder to transfer than less ambiguous knowledge. Williams (2007) concludes that knowledge transfer is context dependent and highlights the need for companies to replicate and adapt knowledge. He argues that the receiving unit in the knowledge transfer has to decide how to allocate its effort: to be more like the sending unit's operations (replication) or changing its operations to integrate with local context (adaptation) (Williams 2007). His analysis is based on the assumption of plant heterogeneity. However, it remains unclear how different levels of plant heterogeneity influence knowledge transfer within manufacturing networks.

Another issue raised by Williams (2007) is that production processes are often complex and production managers can find it difficult to understand the interaction between individual decisions or activities. Knowledge transfer within such complex production environments also seems to be increasingly difficult. However, it remains to be shown through which mechanisms complexity influences knowledge transfer within manufacturing networks.

The remainder of this article is structured as follows. Section 2 reviews the related literature. Section 3 introduces our computational model. In Section 4, we analyze the impact of complexity (Experiment 1) and plant heterogeneity (Experiment 2) on knowledge transfer. Finally, in Section 5 we conclude by discussing our results and implications.

2. Literature Review

From the late 1970s to the early 1990s, operations management research moved from a single-plant perspective to a multi-plant focus and finally toward networks (Rudberg and Olhager 2003). While supply chain management concentrates on the number of organizations and the links between the organizations, manufacturing network theory focuses on the number of plants within a single company and the links between the plants (Rudberg and Olhager 2003). The internationalization of manufacturing networks makes the coordination of geographically dispersed production plants an important objective of the global plant manager. De Toni et al. (1992) highlight that the coordination of decentralized units can be an important source to achieve competitive advantages. In particular, knowledge transfer is important because companies not only have to invent or improve products within the R&D department but also must efficiently communicate generated knowledge to the production plants.

The plant that distributes knowledge throughout the network is the lead factory (Ferdows 1989). The lead factory focuses on exploring new knowledge as it produces the prototype and develops the production processes. Subsequently, this newly generated knowledge is transferred to the geographically distributed production plants, which then focus on exploitation as they adapt and improve the knowledge about the production processes and start pro-

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ducing the serial product. Depending on the need for capacity, there can be many knowledge receiving plants (Rudberg and West 2008). Japanese automotive manufacturers are prominent examples of firms that successfully implemented such a network configuration with a lead factory and multiple production plants (e.g., Simon et al. 2008).

The relevant knowledge transferred between plants can be described as production knowledge (Ferdows 2006), which is needed to translate R&D knowledge into the final product (Cheng et al. 2008). Knowledge transfer within internal manufacturing networks has been analyzed from different perspectives. Tsai (2001), for instance, shows that the position of a subsidiary in the network is crucial for the amount of knowledge that this subsidiary can absorb. Furthermore, knowledge is especially difficult to spread across different subsidiaries if preexisting relationships among subsidiaries are missing (Szulanski 1996). Vereecke et al. (2006) analyze types of subsidiaries in transnational networks according to the knowledge exchange (inflow and outflow) between the different sites. They conclude that the quality of the relationship between two subsidiaries is a major factor in the exchange of innovations, and an established relationship usually works in both directions. In a static analytical model that does not include complexity or plant heterogeneity, Deflorin et al. (2012) show which factors determine the performance of a manufacturing network.

By taking into account the context dependency of knowledge, plant heterogeneity is an important factor to consider (Williams 2007). Based on a case study, Maritan and Brush (2003) conclude that differences in resource endowments may influence the knowledge transfer outcome. In addition, several studies support the notion that complexity raises barriers to transferring knowledge (Rivkin 2000, Williams 2007).

3. Model

To examine the performance implications of knowledge transfer in a multi-plant manufacturing network, we implement a standard NK landscape model. Stuart Kauffman and his colleagues initially developed the model in the context of evolutionary biology (Kauffman 1993, Kauffman and Levin 1987). Since Levinthal (1997) applied this model to management studies, research utilizing the NK framework has been conducted on a broad range of topics such as innovation (Almirall and Casadesus-Masanell 2010, Fleming and Sorenson 2001, Sommer and Loch 2004), new product development (Chao and Kavadias 2008), organizational design (Gavetti 2005, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003), and strategy (Csaszar and Siggelkow 2012, Levinthal and Posen 2007, Siggelkow and Rivkin 2005). McCarthy (2003, 2004) and McCarthy and Tan (2000) show that the NK landscape model also can be applied to operations management by regarding manufacturing firms as complex adaptive systems. They were the first to relate the fitness landscape theory to the process of manufacturing strategy by developing a conceptual model of manufacturing fitness. We take their work as a starting point and extend it by explicitly modeling a multi-plant manufacturing network and analyzing the performance implication of knowledge transfer within such a network.

3.1. Complex Production Processes and Local Search for Better Solutions

The starting point of our NK model is an N-dimensional vector $\boldsymbol{p} = (p_1, p_2, .., p_N)$ of binary production decisions $p_i \in \{0,1\}$ with $i \in \{1,..,N\}$, yielding a total of 2^N possible combinations of decisions. In our model, the vector $\boldsymbol{p}$ represents the production setting, i.e., the set of all relevant decisions made within the production process of a product. The relevant production decisions cover three dimensions: (i) Decisions about the product itself including technical characteristics such as product specifications and use of raw material. (ii) Decisions about the production process including the use of manufacturing technology, process time, and sequences. (iii) Decisions about the management of different production steps, including how to organize production systems, the cooperation with other functions, and suppliers (Cheng et al. 2008).

We illustrate these production decisions with the example of a European manufacturer that produces a certain pipe system. The production decisions comprise, among others, the use of manufacturing technologies and tools. The production of pipe systems requires cutting, bending, forming, welding, and annealing technologies. Specifically, the manufacturer has to make the following decisions: automated or non-automated welding (Decision 1); sleeve welding, welding by extrusion, or laser welding (Decision 2); automated or manual loading of the welding installation (Decision 3); delivery of tools from supplier A or B (Decision 4); and choice of machine adjustments (Decision 5). While some production decisions are independent, others are highly interdependent. The machine adjustments, for example, depend on the choice of supplier because tools from different suppliers require slightly different machine handlings. Analogously, the choice of welding technology (sleeve, extrusion, or laser) is interdependent with the choice of tool suppliers because the effectiveness of different tools depends on the applied welding technology. The decision to load the welding installation manually or automatically is independent of the other production decisions. Even though some decisions (e.g., technology) are not binary choices, they can easily be replicated by a string of binary decisions.

The interdependence between the production decisions is characterized by the parameter $K \in \{0,.., N-1\}$, which describes the number of binary decisions p_j that (co-)determine the performance effect of decision p_i. This effect is characterized by the contribution function $c_i = c_i\ (p_i,\ p_{i1},\ p_{i2},..,p_{iK})$, where $i_1, i_2 \ldots, i_K$ are K distinct decisions other than i. The realizations of the contribution function are drawn from a uniform distribution over the unit interval, i.e., $c_i \sim U[0;1]$. The lowest value, $K = 0$, implies that the production decisions do not depend on each other, and the highest value $K = N-1$ implies that each production decision depends on all other decisions. The performance of the production process for a given production setting $\boldsymbol{p}$ is calculated as the arithmetic mean of the N contributions c_i according to the performance function

$$\pi(p) = \frac{1}{N}\sum_{i=1}^{N} c_i(p).$$

To improve its performance, the firm engages in a process of local search (Levinthal 1997). Following standard procedure, local search involves randomly changing a single production decision. If a new production setting improves performance, it is adopted and the search continues from this new setting in period $t + 1$ (adaptation). Otherwise, the next search step starts from the unchanged setting defined in period t (no adaptation). This process can be interpreted as a search for better positions on a high-dimensional performance landscape (“hill climbing”). A landscape represents a mapping from all 2^N possible outcomes of the production setting onto performance values. We normalize each landscape to the unit interval such that the mean value of the normalized landscape equals 0.5 and the global maximum equals 1.0 (Csaszar and Siggelkow 2012, Rivkin and Siggelkow 2003). The “local peaks” (good solutions) on the performance landscape represent production settings for which a firm cannot improve its performance through local search (Levinthal 1997). The “global peak” is the highest of all local peaks in the landscape and represents the best solution.

The parameter K is commonly interpreted as a measure for complexity (Rivkin and Siggelkow 2003, Siggelkow and Rivkin 2005). It is well known that the number of local peaks increases with complexity K (Kauffman 1993): The lowest value $K = 0$ produces a smooth performance landscape with a single local peak equal to the global peak, whereas the highest value $K = N - 1$ produces a rugged landscape with multiple local peaks. When K increases, the performance of the peaks decreases close to the average performance in the landscape. Kauffman (1993) refers to this phenomenon as the “complexity catastrophe.”

3.2. Multi-Plant Manufacturing Network and Heterogeneous Performance Landscapes

We model a manufacturing network that is composed of one lead factory L and E geographically separated production plants $e \in \{1,\ldots,E\}$. The lead factory and the plants operate in (potentially) different but correlated environments. We conceptualize these heterogeneous plant environments through correlated landscapes and measure the degree of heterogeneity between the landscapes with the parameter $h \in [0,1]$, where a larger value of h represents a higher heterogeneity between landscapes. If $h = 1$, then the landscapes are completely unrelated; $h = 0$ represents a situation in which the landscapes are identical. We generate the correlated landscapes in the spirit of Siggelkow and Rivkin (2005) in that all the contribution values of the landscape are affected by the transformation. However, we slightly modify their approach to ensure that the distribution of the contribution values in the generated landscape remains uniformly distributed, which is a central assumption of the NK model.

Our procedure to generate correlated landscapes consists of adding a certain amount of “noise” to all possible outcomes 2^{K+1} of each contribution c_i. We denote by c_{ij} the j-th outcome of the i-th contribution, with $j \in \{1,\ldots,\ 2^{K+1}\}$. Starting from the initial contribution value c_{ij}, we compute the correlated contribution value $\bar{c}_{ij}$ in two steps. First, we add a random value v that is uniformly distributed in the interval $[-h;+h]$ to the initial contribution c_{ij} and obtain $c'_{ij} = c_{ij}+v$, where $v = 2(u - 0.5)h \sim U[-h;+h]$ and $u \sim U[0;1]$. Second, we confine c'_{ij} to the unit interval through a symmetrical transformation around the closest boundary value (either 0 or 1) and obtain the final correlated contribution value $\bar{c}_{ij}$ with

$$\bar{c}_{ij} = \begin{cases} |c'_{ij}| & \text{if } c'_{ij} < 0 \\ c'_{ij} & \text{if } 0 \le c'_{ij} \le 1 \\ 2 - c'_{ij} & \text{if } c'_{ij} > 1 \end{cases}$$

This procedure of generating correlated landscapes has the following properties: (i) the new contribution value stays in the neighborhood of the initial contribution value (“locality”), (ii) the new contribution value is confined to the unit interval [0,1] (“confinement”), and (iii) the uniform distribution in the unit interval of all contribution values in the initial landscape is also preserved in the correlated landscape (“preservation of distribution”).

3.3. Knowledge Transfer, Adaptation Costs, and Performance of Manufacturing Network

A standard assumption in NK models is that firms initially possess no information about the shape of the performance landscape. Consequently, firms start their search process from a random position on the landscape. In our model, we assume that the production plants do not start from a random position because they can benefit from production knowledge that is generated in the lead factory. As mentioned earlier, the lead factory acts as an intermediary between R&D and the geographically dispersed plants and translates R&D knowledge into production knowledge (Simon et al. 2008). Thus, the geographically dispersed plants receive already tested production knowledge from the lead factory.

We conceptualize the knowledge created in the lead factory as follows. Starting from a random position, the lead factory searches during T periods for improvements in the production process and then (partially) transfers its knowledge to each production plant. This knowledge transfer is characterized through the number of decisions $S \in \{0,\ldots,N\}$ that are transferred in $t = 0$ from the lead factory's production setting $\boldsymbol{p}^*_L = (p^*_{L,1}, p^*_{L,2},.., p^*_{L,N})$ after T periods of (local) search. We refer to S as the extent of the knowledge transfer and assume that the knowledge transfer results in one-time transfer costs for each plant given by $TC(S)$. In our main experiment, we consider strictly convex transfer costs with $TC'(S) > 0$ and $TC''(S) > 0$. Thus, the transfer costs increase with an increasing rate in the number of decisions transferred from the lead factory to the other plants. We assume that the global plant manager can control the extent of knowledge transfer, i.e., s/he can decide how many production decisions are transferred from the lead factory to the plants. In addition, we assume that the S production decisions transferred are randomly drawn from the lead factory's production setting $\boldsymbol{p}^*_L$.

As a result of the knowledge transfer in $t = 0$, the initial position of production plant e in $t = 1$ is a vector $(p^*_{L,1},\ldots, p^*_{L,S}, p_{e,S+1}.., p_{e,N})$ that corresponds in S decisions to the production setting of the lead factory. Thus, $S = N$ represents the situation of a complete knowledge transfer where the lead factory transfers all production decisions to the E plants. In this case, each production plant starts its search process in $t = 1$ from the (final) production setting of the lead factory. In contrast, $S = 0$ represents a situation in which no knowledge is transferred from the lead factory to the E plants such that each plant starts its search process in $t = 1$ from a random position. The remaining N–S production decisions that are not transferred are randomly chosen in each plant. We assume that each plant can change all N production decisions in the subsequent local search process, i.e., we do not assume that the plants have to stick to the production setting $(p^*_{L,1}, \ldots, p^*_{L,S})$ that was transferred from the lead factory.

As mentioned in the introduction, machine adjustments can lead to adaptation costs in the production plants. We extend the standard NK model by integrating such adaptation costs as follows: after the knowledge transfer, we assume that each actual implementation (but not the evaluation) of a new production setting in the plants is associated with adaptation costs given by the cost parameter $\alpha > 0$. Accumulated adaptation costs until and including period t amount to $AC(t) = \alpha\Gamma_e(t)$, where $\Gamma_e(t)$ denotes the number of total adaptations of the production setting $\boldsymbol{p}$ in plant e. It should be noted that the adaptation costs have no effect on the search process because these costs incur only for the implementation, and not the evaluation of a new production setting. We assume that the evaluation of a new production setting does not require making a significant change to the current production setting, but can be realized in a hands-on manner, e.g., based on simulations, theoretical calculations, thought experiments, discussions/meetings among employees and the management. The costs that such "off-line" search (Winter et al. 2007) generate are negligible compared with the adaptation costs that incur for the actual implementation of a new production setting.

The total performance Π of the manufacturing network in $t \in \{1,\ldots,P\}$ is calculated as

$$\prod(t) = \sum_{e=1}^{E}\{\pi_e(p_e(t)) - AC_e(t) - TC(S)\},$$

where π_e is the performance of plant e, $AC_e(t)$ are the accumulated adaptation costs of plant e, and $TC(S)$ represents the transfer costs for each plant. Following the literature on NK models, we interpret the performance of the manufacturing network as financial performance (Levinthal 1997). The lead factory is not included in the performance calculation because we assume that after the knowledge transfer, the lead factory turns its attention to a new product and generates production knowledge for this product through a process of local search. Similarly, we do not account for the lead factory's adaptation costs in the performance calculation. However, the qualitative pattern of results would not change if we included the lead factory in the performance calculation. See the sensitivity analysis in the online appendix for more detail.

Figure 1 provides a high-level overview of our model.

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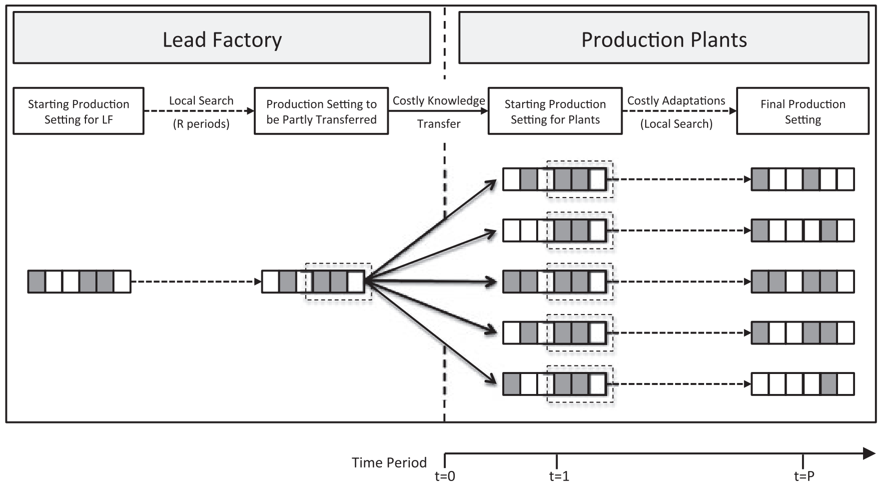
Figure 1 Overview of Model



4. Analysis

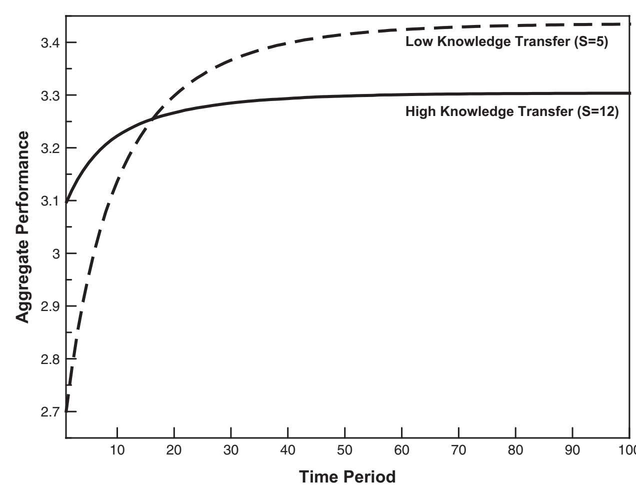
In the following sections, all simulations have $N = 15$ and we base our results on the average performance over 100,000 independent runs (i.e., landscapes) of the simulation model to guarantee that the reported differences are inherent to our model rather than the results of a stochastic process. This procedure ensures that the reported simulation results are statistically significant at the 1% level. Unless mentioned otherwise, we implement quadratic transfer costs $TC(S) = \tau S^2$ and fix the transfer cost and adaptation costs parameters to intermediate values, i.e., $\tau = 0.001$ and $\alpha = 0.03$, respectively. We further set $T = 200$, i.e., the lead factory searches during 200 periods for improvements in the production process and (partly) transfers its production knowledge in $t = 0$ to the plants. We analyze a manufacturing network with $E = 5$ production plants and set plant heterogeneity to $h = 0.1$. We observe the network for $P = 200$ periods, which is sufficient because more than 99% plants have then reached steady state (local or global peak). Examining steady-state performance is justified for products with long product life cycles. In the online appendix, we provide sensitivity analyses of our results to alternative model initializations and specifications.

4.1. Experiment 1: Performance Implications of Knowledge Transfer and the Moderating Effect of Complexity

In Experiment 1, we seek to understand the baseline properties of the model. First, we examine how the performance of the manufacturing network evolves over time. Second, we analyze how the complexity of the production process affects long-run performance.

Figure 2 displays the performance evolution of the manufacturing network over time (from $t = 1$ until $t = 100$) for a production process with very low complexity ($K = 2$) and the above given model specifications. Because beyond period $t = 100$, total performance is almost flat, we focus on $t \in \{1,\ldots,100\}$ in Figure 2. The dashed line (solid line) reports the network's performance if the lead factory has transferred $S = 5$ ($S = 12$) production decisions to the E production plants in $t = 0$.

Figure 2 Performance Evolution



The figure shows that in $t = 1$ the manufacturing network starts with a higher initial performance if, in $t = 0$, the lead factory has transferred $S = 12$ instead of $S = 5$ production decisions to the plants. After the knowledge transfer from the lead factory, the performance of the manufacturing network increases steadily from period to period as the plants acquire additional knowledge to improve their production process, where the marginal performance improvements gradually decrease from period to period. Even though the manufacturing network has started with a low initial performance in the case of a less-complete

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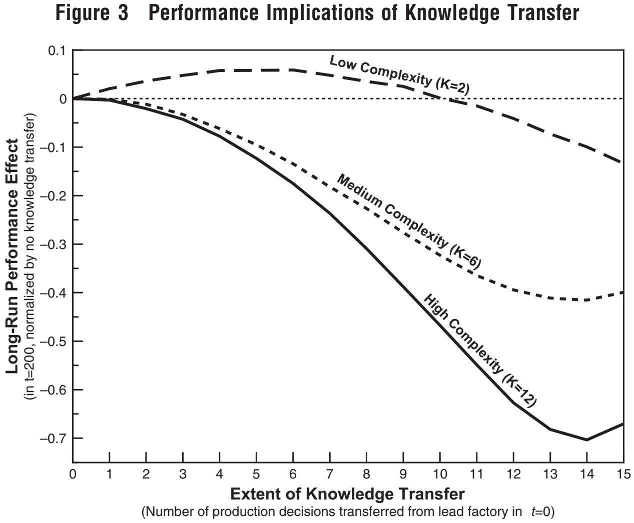
knowledge transfer (S = 5), the network achieves superior long-run performance compared with a more-complete knowledge transfer (S = 12).

In general, the initial performance in t = 1 depends on two opposing effects—a negative transfer cost effect and a positive knowledge effect. Both effects depend on the extent of knowledge transfer, represented by the number of decisions S that are transferred from the lead factory to the plants. A transfer of more decisions results in higher transfer costs (transfer cost effect), but also improves the initial performance of the production plants (knowledge effect). If only a small number of decisions are transferred from the lead factory to the other plants, total transfer costs will remain small. A small number of transferred decisions also mean that the other plants can benefit from only a few of the production improvements which have been realized in the lead factory, and therefore, they have to start from a lower position on their landscapes. As we will see below, starting from a lower position on the landscape also implies that a plant will have to incur higher accumulated adaptation costs to improve its performance in the remaining periods.

Next, we examine the interplay between the extent of knowledge transfer and the complexity of the production process. Figure 3 provides a systematic analysis of the long-run performance implications (y-axis) for the full range of S (x-axis), i.e., from no knowledge transfer (S = 0) to complete knowledge transfer (S = 15). The performance is normalized and reflects the difference between total performance if the lead factory transfers knowledge (S > 0) and the benchmark performance without knowledge transfer (S = 0) for different levels of complexity. The dashed line represents the performance implications for production processes with low complexity (K = 2); the dotted and solid lines indicate the implications for production processes with medium (K = 6) and high (K = 12) complexity, respectively.

Figure 3 Performance Implications of Knowledge Transfer



The figure shows that the level of complexity crucially influences the performance implications of knowledge transfer in a manufacturing network. Interestingly, we observe an inverted U-shaped relationship between the extent of knowledge transfer and long-run performance for production processes with a low level of complexity (K = 2), an (almost) linear relationship for production processes with medium complexity (K = 6), and a U-shaped relationship for production processes with high complexity (K = 12). More specifically, for low levels of complexity, the manufacturing network can benefit from the knowledge transfer and the performance effect reaches its maximum for a moderate extent of knowledge transfer (S = 5). Negative effects of knowledge transfer materialize only when knowledge transfer is extensive (i.e., S > 10). For medium and high levels of complexity, performance is reduced, rather than enhanced, if the lead factory transfers knowledge to the other plants, independent of the extent of knowledge transfer.

In the remainder of this section, we seek to uncover the mechanisms underlying the effect of knowledge transfer on total performance.

4.1.1. Decomposing the Effect of Knowledge Transfer on Performance. To uncover the mechanisms, we decompose the performance implications of knowledge transfer (in Figure 3) into two components: (1) a cost-saving effect driven by a lower number of adaptations due to the knowledge transfer; and (2) a transfer cost effect driven by the costly knowledge transfer itself. Figure 4 displays the performance implications of the two opposing effects (y-axis) as a function of the extent of knowledge transfer (x-axis). The dotted line reflects the performance implications of the transfer cost effect, while the dashed line reports the performance implications of the cost-saving effect. The net effect of these two components of the knowledge transfer is plotted as the solid line, fully reconstructing the main result in Figure 3. We differentiate between production processes with low complexity (K = 2) in Panel (a) and high complexity (K = 12) in Panel (b).

The figure shows that the performance implications of the cost-saving effect are always positive, while the performance implications of the transfer cost effect are unambiguously negative. For a production process with low complexity (Panel a), the plants benefit via the cost-saving effect (dashed line) from each transferred decision. This is not the case for high complexity (Panel b). Here, the transfer must be relatively extensive before the plants can take advantage of the

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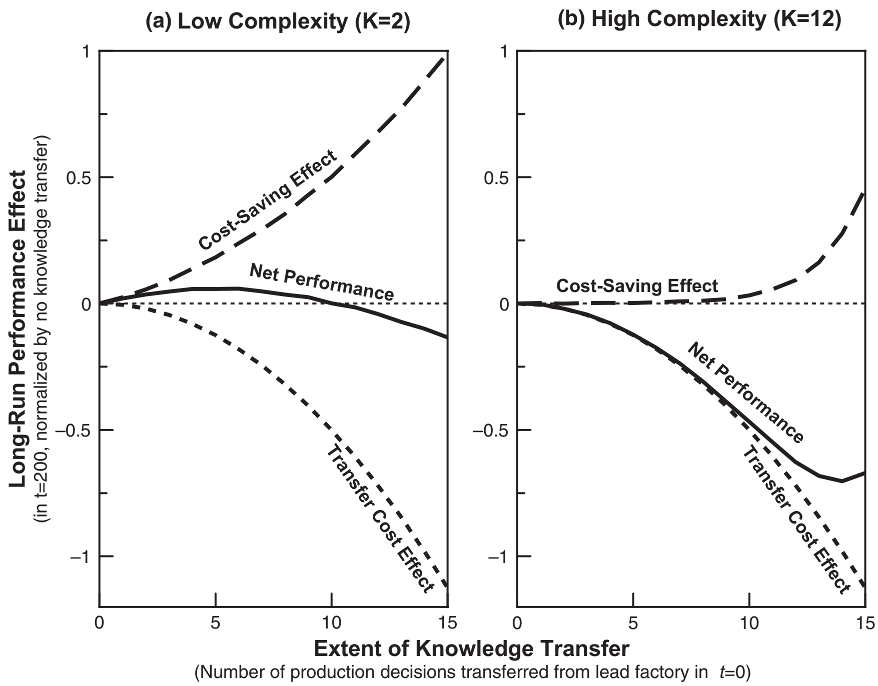
Figure 4 Decomposing the Effect of Knowledge Transfer



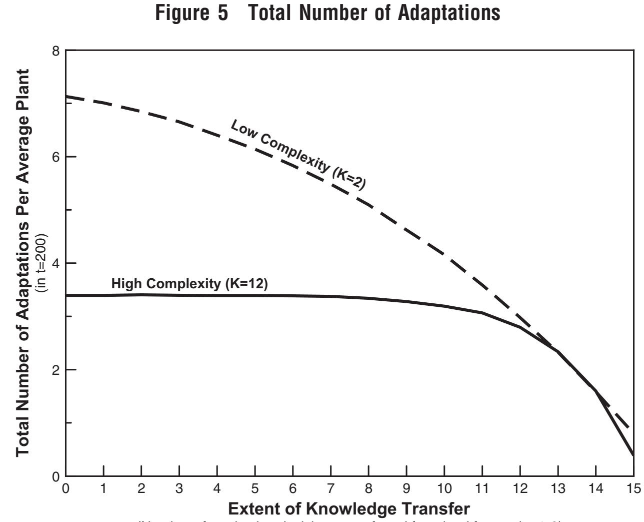
lead factory's production knowledge: The dashed line in Panel (b) is flat until $S = 9$. Nevertheless, each transferred decision implies transfer costs that reduce performance independent of complexity (dotted line). Next, we seek to uncover the mechanisms underlying the transfer cost and cost-saving effects.

4.1.2. The Transfer Cost Effect. The transfer cost effect is straightforward because transfer costs are simply a convex function of the number of transferred decisions (extent of knowledge) given by $TC(S) = \tau S^2$. Thus, $[-TC(S)]$ is a decreasing function in S, where τ controls the curvature of this function. The transfer cost effect is independent of the level of complexity.

The transfer costs effect, and thus, the performance implication of the knowledge transfer would change if we considered a concave transfer cost function $TC(S)$ with $TC'(S) > 0$ and $TC''(S) \leq 0$. In the case of concave transfer costs, we find that it is either optimal to transfer all production decisions from the lead factory (for a sufficiently low τ) or it is optimal not to transfer production knowledge from the lead factory (for a sufficiently high τ), but to build it up in each plant. In contrast, for a convex cost function an interior solution can exist (depending on the complexity of the production process) so that it can be optimal to transfer an intermediate level of knowledge. A concave cost function characterizes a scenario with high fixed costs (e.g., necessity to fly a team across to the other plant), while a convex cost function represents a scenario where the knowledge transfer becomes increasingly costly the more details one has to transfer.

4.1.3. The Cost-Saving Effect. To explain the cost-saving effect, we first analyze how the extent of knowledge transfer affects accumulated adaptation costs. Figure 5 reports the total number of adaptations per plant after 200 periods (y-axis) as a function of the extent of knowledge transfer (x-axis) for low complexity ($K = 2$, dashed line) and high complexity ($K = 12$, solid line), respectively. To compute the accumulated adaptation costs, one simply has to

Figure 5 Total Number of Adaptations



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multiply the total number of adaptations with the cost parameter α.

We find that the total number of adaptations per plant decreases with higher complexity K for a given extent of knowledge transfer. Increasing complexity renders the landscape more rugged, and thus, the firms get trapped easier at a local peak resulting in fewer adaptations. The dashed line shows that for production processes with low complexity ($K = 2$), each plant changes on average approximately 7.1 production decisions until $t = 200$ if no knowledge is transferred from the lead factory. The number of adaptations decreases to 3.1 for production processes with high complexity ($K = 12$, solid line).

Moreover, the total number of adaptations per plant decreases with a more extensive knowledge transfer, independent of complexity: The higher the number of decisions transferred from the lead factory to the plants, the better the plant's starting position on the performance landscape in $t = 1$ (knowledge effect), and the fewer adaptations are necessary in each plant before it finds a good solution. As a consequence, the corresponding adaptation costs decrease and result in a positive cost-saving effect. However, the knowledge effect diminishes over time because in the long run, the plants end up (on average) at the same production setting they would have found without transferring knowledge. While the knowledge effect has no direct impact on long-run performance, it has an impact on the cost-saving effect because it affects how plants adapt their production process.

While the total number of adaptations per plant almost linearly decreases in the extent of knowledge for a production process with low complexity (dashed line), for high-complex production processes this number remains flat (solid line) until the transfer is relatively complete (S = 9) and then decreases with an increasing rate. A more complex production process means more decisions are interdependent and, as a consequence, the plants benefit from the lead factory's production knowledge only if the transfer is relatively complete.

To fully reconstruct the cost-saving effect, we subtract from the benchmark performance (no knowledge transfer) the accumulated adaptation costs. Because a more extensive knowledge transfer lowers the accumulated adaptation costs, the resulting cost-saving effect is positive and increases in the extent of knowledge transfer.

In sum, this experiment shows that the performance implications of knowledge transfer in manufacturing networks is driven by two interacting mechanisms: The positive cost-saving effect and the negative transfer cost effect. The complexity of the production process moderates the impact of the knowledge transfer on the cost-saving effect in a non-linear fashion.

4.2. Experiment 2: The Moderating Effect of Plant Heterogeneity

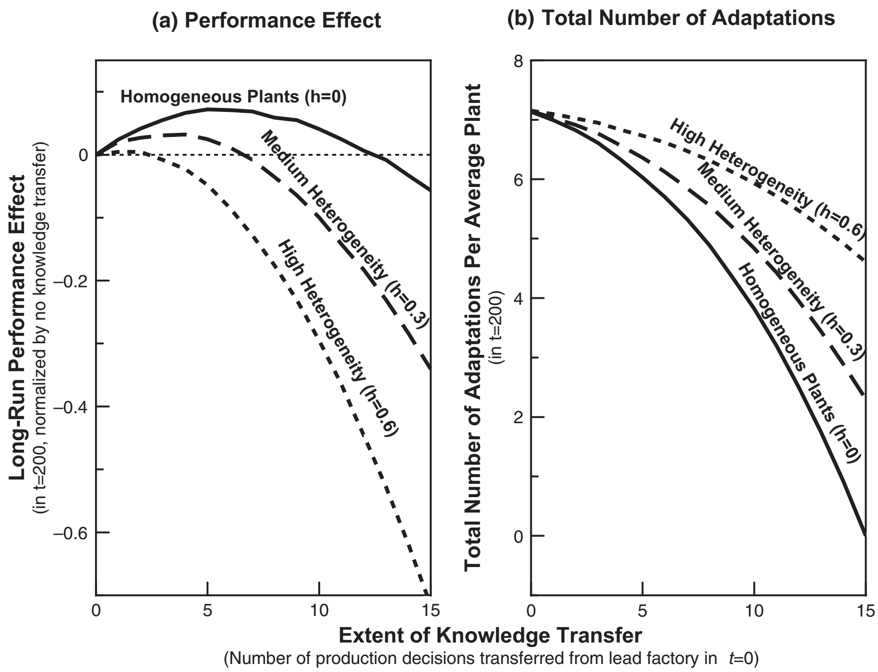
In Experiment 1, we analyze production plants that operate on moderately heterogeneous landscapes ($h = 0.1$) and find that the performance implications of the knowledge transfer crucially depend on the complexity of the production process. In Experiment 2, we explore how plant heterogeneity moderates the performance implications of knowledge transfer. To isolate the effect of plant heterogeneity on performance, we rerun Experiment 1 and vary the level of heterogeneity between the lead factory and the plants, but we hold constant the complexity of the production processes and consider only low complexity ($K = 2$).

Figure 6(a) displays the long-run performance implications (y-axis) for the full range of S (x-axis). The performance is normalized and reflects the difference between total performance if the lead factory transfers knowledge ($S > 0$) and the benchmark performance without knowledge transfer ($S = 0$) for different levels of plant heterogeneity. The solid line represents the performance implications for homogeneous plants ($h = 0$); the dashed and dotted lines indicate low ($h = 0.3$) and high ($h = 0.6$) levels of heterogeneity, respectively.

The degree of heterogeneity between the lead factory and the plants has a strong impact on the performance implications of knowledge transfer. Not surprisingly, the positive effects of the knowledge transfer decreases with plant heterogeneity. However, in contrast to complexity, plant heterogeneity moderates the impact of knowledge transfer in a linear way. To examine the underlying mechanisms regarding the interplay between the extent of knowledge transfer and the number of adaptations in the heterogeneous plants, we provide Figure 6(b), which reports the total number of adaptations (y-axis) after 200 periods for the full range of S (x-axis) and different levels of plant heterogeneity. We make the following observations. First, for a given extent of knowledge transfer, the total number of adaptations decreases as plant heterogeneity decreases. Second, the total number of adaptations decreases almost linearly with a more extensive knowledge transfer.

We conclude that the complexity of the production process and the degree of heterogeneity between the plants qualitatively have a similar impact on the performance implications of a knowledge transfer in manufacturing networks. Both a lower production complexity and lower plant heterogeneity tend to increase the usefulness of the production knowledge generated in the lead factory, and thus, the benefits of a transfer by lowering the number of adaptations in the plants. While complexity affects the number of

Figure 6 Moderating Effect of Plant Heterogeneity



adaptations subsequent to the knowledge transfer in a non-linear way, plant heterogeneity does so in a linear way.

5. Conclusions and Future Research

This study formally examines the performance implications of knowledge transfer in multi-plant manufacturing networks with a lead factory. Using an NK landscape model, we analyze under which circumstances and to what extent it is beneficial to create production knowledge within a lead factory and transfer it to geographically dispersed plants. We demonstrate that the knowledge transfer generates a trade-off between a positive cost-saving effect due to fewer adaptations in each plant, and a negative transfer cost effect due to the costly knowledge transfer itself. The relative strength of these two effects determines the performance implications of the knowledge transfer. The complexity of the production process and the heterogeneity among plants affects the usefulness of the production knowledge generated in the lead factory, and thus, they determine the extent to which the plants must adapt their production process subsequent to the knowledge transfer. Both the complexity and the heterogeneity therefore moderate the impact of the cost-saving effect and determine whether the knowledge transfer from the lead factory to the plants is beneficial. While complexity moderates the performance implications of knowledge transfer in a non-linear way, plant heterogeneity does so in a linear way. Table 1 summarizes our main results.

Our research contributes to the existing literature in several ways. Research on manufacturing network configuration and coordination suggests that knowledge transfer is important (Szulanski 1996, Tsai 2001, Vereecke et al. 2006). We add to this literature because we not only highlight the importance of knowledge transfer, but we enhance the understanding of what may constitute important moderators. While Vereecke et al. (2006) emphasize the quality of the relationship between two subsidiaries as a major factor, we argue that the complexity of the production process crucially determines the performance implications of the knowledge transfer. Moreover, Meijboom and Vos (1997) ask whether coordination problems can alter the configuration in manufacturing networks. Our results confirm that coordination problems can indeed imply the necessity for changes in the network configuration. If, for example, a manufacturing network achieves higher performance without any knowledge transfer, the lead factory becomes obsolete. We support the notion that configuration and coordination of manufacturing networks should be studied as interlinked instead of isolated dimensions (Meijboom and Vos 1997, Porter 1986, Rudberg and Olhager 2003).

While we analyze knowledge transfer within a manufacturing network, our insights are transferable to other settings that consist of a knowledge sending and receiving unit. Our study may contribute to the literature on knowledge management, which suggests

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Table 1 Summary of Main Results

Condition	Result	Explanation
For production processes with low complexity…	… knowledge transfer can enhance performance. … a complete knowledge transfer is not optimal.	Plants can always take advantage of production knowledge from lead factory so that each transferred decision reduces adaptation costs. Thus, positive cost-saving effect can compensate for negative transfer cost effect.
For production processes with medium-to-high complexity…	… knowledge transfer reduces performance. … it is optimal not to transfer any knowledge from lead factory to plants.	Plants can only take advantage of production knowledge from lead factory if knowledge transfer is extensive, otherwise transfer has no effect on adaptation costs. Yet, in case of extensive knowledge transfer, resulting transfer costs are high and outweigh benefits of cost-saving effect.
For a network with lower/ higher plant heterogeneity….	… knowledge transfer is more/less beneficial.	Usefulness of production knowledge from lead factory linearly decreases with plant heterogeneity. Thus, higher/lower plant heterogeneity weakens/ strengthens positive cost-saving effect, but has no effect on transfer cost effect.

that performance gains from knowledge transfer can depreciate rapidly (Argote 1999, Darr et al. 1995, Williams 2007). We refine these findings by showing that the knowledge effect indeed diminishes over time and the extent of knowledge transfer has no direct effect on long-run performance. However, the knowledge effect has an impact on how plants adapt their production process after the knowledge transfer.

Our study may also contribute to the literature on absorptive capacity, which mainly focuses on alliances and supply chains (see Volberda et al. 2010 for a literature review), but less attention has been paid to the role of manufacturing networks. To understand the mechanisms and dynamics through which knowledge transfer affects performance of manufacturing networks, we decomposed the performance implications into the transfer cost effect and the cost-saving effect. A high level of absorptive capacity in the receiving unit may be associated with a particularly pronounced cost-saving effect because the production knowledge of the sending unit can be absorbed more easily, reducing the number of adaptations in the receiving unit. By assuming such a positive correlation between the level of absorptive capacity and the strength of the cost-saving effect, our study may help to enhance the understanding of how absorptive capacity affects knowledge transfer in multi-plant manufacturing networks.

From a managerial perspective, our study provides the following insights. Any measure that reduces complexity supports the effectiveness of knowledge transfers within a manufacturing network with a lead factory and should be taken into account. However, if the company faces complex production processes whose complexity cannot be reduced, the company should invest in methods that support a complete knowledge transfer. For example, the assignment of knowledge transfer experts who are responsible for accompanying the knowledge transfer should be taken into account. Moreover, the lower the interdependencies between the production decisions, the easier it is for plants to implement changes and to build up the required capabilities to recognize and implement the necessary adaptations. Our results suggest that it is important to continuously develop the capabilities of the receiving plants. Although the capability base of the lead factory is on a higher level, the need to adapt the transferred knowledge reveals the importance of investing in the capabilities of the receiving plants, particularly, their absorptive capacity. Our results may provide insights about when investment in absorptive capacity of the receiving unit can be beneficial.

In sum, our results indicate that the knowledge transfer in multi-plant manufacturing networks plays a central role and has important implications for the network configuration. Our model can be extended in several directions. First, it would be interesting to further enhance our understanding of how different choices of network configuration (size of the plants and size differences between the plants, location, and scope) influence the knowledge transfer outcome. Second, we encourage the integration of learning curve effects into our model. Lapré and Wassenhove (2001) argue that production units in a single firm do not necessarily have identical learning rates. Translated to our model, this would mean that there is heterogeneity among production plants regarding their capacity to absorb production knowledge from the lead factory. Explicitly modeling different levels of absorptive capacity in the plants could provide interesting insights. Third, it may be fruitful to examine the optimal timing of the knowledge transfer in more detail. For example, Mihm et al. (2003) find that communication of preliminary information between employees can be beneficial in large and complex projects. Fourth, looking at the accumulated performance over all periods rather than the steady-state performance could provide new insights for the implications of knowledge transfer—especially for products

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with short life cycles. Fifth, it would be interesting to examine a setting in which the global plant manager can choose to transfer clustered production decisions (based on the underlying interaction pattern). Finally, a promising avenue for future research would be the integration of evaluation costs into our model. Depending on the industry sector, not only the adaptation but also the evaluation of a new production setting may be costly.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Online Appendix: Sensitivity Analysis

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