The lead factory concept: benefiting from efficient knowledge transfer

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Abstract

Purpose – The purpose of this paper is to compare two distinct network structures to determine and show which structure is more profitable. Specifically, it aims to show which factors render the lead factory concept advantageous.

Design/methodology/approach – Based on a simple, two-stage model for prototype and serial production, the authors highlight factors that determine the relative advantages and disadvantages of the lead factory concept in comparison to an archetype network. The archetype network mirrors those networks that have not implemented special strategic plant roles.

Findings – The analysis shows that the lead factory concept benefits from an efficient knowledge transfer. Particularly, it is more profitable than the archetype network under the following conditions: there are a high number of production plants; the adaptation costs for implementing the transferred prototype from the lead factory to the plant are low; the manufacturing costs for the prototype are high; and the manufacturing processes are not highly specific or knowledge intensive.

Originality/value – The paper enables better understanding of the conditions under which the lead factory concept is advantageous for transferring knowledge within an intra-firm network.

Keywords Knowledge transfer, Manufacturing industries, Factories, Lead factory, Network

Paper type Research paper

1. Introduction

Currently, large industrial companies operate a network of geographically distributed research and development departments (R&D) and manufacturing units to add the benefits of location-based advantages to their preexisting firm-specific advantages. Managers of such R&D and manufacturing networks must solve one of the most intriguing dilemmas in the field of business administration: they must organize these networks to achieve operational efficiency while simultaneously being able to reconfigure the operations of these networks to adapt to new circumstances and explore new opportunities (Benner and Tushman, 2003).

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The extent to which a company can overcome the tension between exploration (R&D) and exploitation (production) crucially depends on the company's ability to create, transfer, and apply relevant knowledge; however, the transfer of knowledge within a company's internationally distributed network is extremely challenging (Tsai, 2001). Although the efficiency of knowledge transfer within production networks depends on many factors, the organization of the network structure plays an important role because it hinders or supports knowledge transfer (Tsai, 2001).

Over the last years, a new form of organizing intra-firm R&D and manufacturing networks has begun to emerge based on the understanding that subsidiaries differ in their tasks and capabilities (Bartlett and Ghoshal, 1989). Various researchers have shown that plants within an intra-firm network can be allocated to different strategic roles (Enright and Subramanian (2007) for an extensive review). Enright and Subramanian's (2007) overview reveals a common role of plants within the network: they identify a single production plant that is strategically important and serves as the central knowledge hub of the network. A widely accepted denotation for this special type of production plant is the lead factory.

Following Ferdow's (1997) definition of lead factories, the task of such a central plant is to create new processes, products, and technologies for the entire company. The lead factory is the only plant that interacts with the R&D department. The lead factory supports the R&D department in the development of new products and processes, and it produces the prototype. The most important task of the lead factory is the generation and transfer of knowledge (Simon *et al.*, 2008).

Prime examples of the lead factory concept are Japanese Original Equipment Manufacturers (Daihatsu, Honda, Isuzu, Mitsubishi, Nissan, Suzuki, and Toyota): overseas plants replicate production processes that are first tried and tested in Japanese plants. Many studies have described the core concept of the lead factory and have explored its activities and responsibilities (Vereecke *et al.*, 2006; Vereecke and Van Dierdonck, 2002; Simon *et al.*, 2008); however, the research to date has failed to explain why such a special plant should be created. An exception is Deflorin *et al.* (2010) who discuss the lead factory concept and its advantages in a conceptual paper. They conclude that the lead factory concept is most useful when matched with an adaptation strategy and for companies producing a product with low knowledge maturity. However, the paper is purely conceptual and does not identify conditions in which the lead factory has a comparative advantage over alternative forms of production networks.

In general, if and under what contingencies the lead factory concept produces concrete advantages over a network without a lead factory remains to be analyzed. Our paper tries to fill this gap in the literature. We aim to show which factors render the lead factory more or less profitable than an archetype network. In our study, profitability refers to production costs (i.e. a production network is more profitable than another if it exhibits lower production costs). To derive the factors that render a lead factory more or less profitable, we compare it to an archetype network. Many networks do not manage their plants according to different plant roles but treat them identically. One of the key characteristics of this type of network is the spatial and structural separation of exploitation and exploration (Raisch and Birkinshaw, 2008). The R&D department contributes exploration activities, and the geographically dispersed production plants focus exclusively on exploitation (Simon *et al.*, 2008). It is assumed that the plants do not differ strategically, even if the plant's location is in close proximity to the R&D department. As this field of research continues to characterize the roles of different types of plants, the need for a better understanding of the factors that render the lead factory concept more or less profitable than the archetype network structure becomes apparent. This research applies to industrial companies with multiple plants, and we assume that these plants produce similar products. The fact that many companies serve the international market from multiple plants renders this assumption plausible. Additionally, this research is of interest to industrial companies that need to produce a prototype to be able to move from R&D to series production.

Within an international distributed R&D and manufacturing network, the efficiency of knowledge transfer is crucial. Different contingencies may render knowledge transfer more advantageous in lead factory-based network structures than in the archetype network; however, this question has yet to be analyzed. Based on a simple two-stage model for prototype and serial production, we identify factors that determine the relative advantages and disadvantages of the lead factory concept in comparison to the archetype network.

The remainder of the paper is structured as follows. The following section describes the theoretical background of knowledge transfer in R&D and manufacturing networks and is followed by a description of the two distinct network structures. Section 3 presents the analytical model of the two distinct network structures. Section 4 describes the primary results of this study, and Section 5 concludes the paper.

2. Theory

2.1 Knowledge transfer in R&D and manufacturing networks

Applying a knowledge-based view to a firm means that a firm's key role is to create, store, and apply knowledge (Grant, 1996). In the field of operations management, the focus is on creating, transferring, and applying operational know-how. Knowledge and knowledge transfer is important for achieving competitive advantage (Grant, 1991). Therefore, a network structure supporting knowledge transfer is preferable. Many managers report that their systems for creating, transferring, and applying manufacturing know-how are often informal; in other words, the systems are *ad hoc* implicit, and not well organized (Ferdows, 2006). This "adhocracy" contrasts with the fact that internal knowledge transfer is an important source of competitive advantage for many organizations (Argote and Ingram, 2000; Kogut and Zander, 1992).

We focus on the knowledge transfer that is inherent to the processes that begin within R&D and the development of new products and end with the production of large volumes. Concretely, R&D first develops a detailed process recipe (Terwiesch, 2004). This process recipe is transferred to production, where production employees have to implement the described processes and improve them in a pragmatic, real-time setting. First, a prototype is produced. If necessary, the process recipe is adapted. Finally, the production of large volumes starts. We define the period from the introduction of a new process into a production facility until the production of large volumes as "ramp-up" (Terwiesch, 2004).

Knowledge transfer is influenced by different factors: for example, the strength of the ties through which knowledge is transferred (Granovetter, 1985) and the absorptive capacity of the recipients (i.e. diversity of backgrounds) (Cohen and Levinthal, 1990). The higher the difference between the sending and the receiving unit, the more difficult it is to transfer knowledge (Gupta and Govindarajan, 2000).

Our research focuses on internationally distributed manufacturing networks. Costs of transforming R&D knowledge into production know-how costs occur whenever the process recipe is transferred from R&D to the different plants. These costs differ within the network, depending the strength of the personal ties between the R&D department and the plants (Granovetter, 1985). Furthermore, the absorptive capacity of the receiving plants differs as a result of the often highly heterogeneous backgrounds, experiences, and knowledge of their workers. Absorptive capacity is the ability to recognize the value of new information, to assimilate it, and to apply it based on the prior related knowledge of the department (Cohen and Levinthal, 1990). The knowledge transfer from the R&D department to plants within the same regional area is usually less cost intensive than the knowledge transfer to plants in distant countries because departments in the same regional area normally have strong relationships that promote knowledge sharing (Tsai, 2001). Furthermore, departments in the same regional area normally possess higher absorptive capacities because their respective backgrounds are similar (Cohen and Levinthal, 1990). We summarize these issues as the heterogeneity of the plants. The higher the heterogeneity (difference) between plants in terms of location, capabilities, processes and equipment, the higher the hurdles for an efficient knowledge transfer. For example, within a network with a high heterogeneity, R&D needs to take into account the specific circumstances of each plant (differences in capabilities, processes or machines) to be able to efficiently transfer the process recipe. In contrast, within a network with low heterogeneity network, the same process descriptions are valuable for all plants. To understand which factors render a lead factory more or less profitable, we therefore distinguish between two scenarios: low heterogeneity and high heterogeneity between plants. We investigate whether networks with a high or low heterogeneity render a lead factory network more or less profitable than an archetype network.

Another factor that is well known to influence knowledge transfer is the property of the knowledge itself (Fleming and Marx, 2006). The property of knowledge divides knowledge into explicit and tacit knowledge (Polanyi, 1967; Nonaka, 1994; Nonaka and Von Krogh, 2009). In contrast to explicit knowledge, tacit knowledge is often unarticulated, as it is tied to senses, movement, skills, physical experiences, intuitions, or implicit "rules-of-thumb" (Hopp *et al.*, 2009). Zander and Kogut (1995) describe the property of knowledge according to its specificity. Knowledge specificity, also described as "system dependence", captures the degree to which a capability is dependent on functional expertise. The lower the system dependency or the higher the ability of the knowledge to stand alone, the easier it is to transfer (Minbaeva, 2007).

The production of a new prototype requires new production knowledge. The new knowledge about the production process includes basic and specific dimensions. The basic dimensions describe new knowledge that can be used by all plant managers regardless of the individual characteristics of their respective plants. Examples of this type of knowledge are the description of allowed tolerances, the production step sequence or the surface requirements of industry-wide welding, brazing or dyeing standards.

The specific dimension describes new knowledge that is idiosyncratic (i.e. its validity depends on the individual characteristics of each plant). Examples for this type of knowledge are the detailed material planning that specifies which raw materials or components are needed in what quantities and when they are required. The timing and amount of raw material and components depend on the machine type, shop-floor layout and employee experience. Therefore, they are dependent on the individual characteristics of each plant.

In summary, we investigate whether a high amount of specific knowledge renders a lead factory network more or less profitable than an archetype network. Additionally, we show how the plant heterogeneity influences the results.

2.2 R&D and manufacturing networks

The efficiency of the knowledge transfer between R&D and manufacturing is largely determined by the structure of the entire R&D and manufacturing network. In this section, we identify the lead factory concept and the archetype network structure as two general models of network structures, and we then characterize them according to their knowledge transfer features.

2.2.1 The lead factory concept. The goal of the lead factory concept is to transform one of the production plants into an "intermediary" between the R&D department and the other geographically distributed production plants (Deflorin *et al.*, 2010). This "intermediary" is called the lead factory. It works closely with the R&D department to facilitate knowledge transfer from exploration (R&D) to exploitation (production). New products, processes, and technologies are developed by the R&D department in collaboration with the lead factory. The lead factory holds an overall mandate for innovation: the production of the prototype and its respective processes are ultimately the responsibility of the lead factory (Enright and Subramanian, 2007). The knowledge generated by the lead factory during its engagement in the development process and the production of the prototype enables the lead factory to "incorporate" substantial amounts of knowledge into the design of the serial production process, which is then transferred to other production plants. The "intermediation" of the lead factory enables other manufacturing units to benefit from knowledge that is generated by the lead factory and is then either explicitly transferred to the production plants or implicitly incorporated into the design of the manufacturing process. As a result, the production plants are able to develop more stable and reliable manufacturing processes. The lead factory also assesses and optimizes the manufacturing methods, trains the staff at new sites, gathers and validates the ideas for optimization, and generally drives continuous improvements (Simon *et al.*, 2008). Within the lead factory concept, the production plant implements the processes developed by the R&D department and lead factory and described in the process recipe. In addition to producing the product, the plants focus on the continuous improvement of the manufacturing processes and if needed, on the adaptation of the product to local requirements. If changes are required, the production plant reports them back to the lead factory, which, in turn, makes the changes either in conjunction with the R&D department or alone and then transfers the solution back to all production plants for which the changes are relevant. In summary, the lead factory is the capability or knowledge creator for the network, whereas the other production plants are capability or knowledge recipients (Enright and Subramanian, 2007; Kogut and Zander, 1992).

2.2.2 The archetype network structure. To understand the factors that render the lead factory concept more profitable, we compare it to an archetype network. This network does not have special strategic plant roles. Each plant works directly with R&D and is responsible for the production ramp-up. This network structure is typical in a localization strategy (Abele *et al.*, 2008). The centrally developed products are further customized to meet local requirements. Therefore, plants produce their respective products independently. Implementing a localization strategy enables a company to achieve a high level of market proximity, which is critical for success in many markets (Meyer and Jacoob, 2008).

One of the key descriptive factors of the archetype network structure is spatial separation. R&D departments and production plants are organizationally separated. This separation permits the R&D department to focus on exploration activities, whereas the production plants concentrate their resources on exploitation (Raisch and Birkinshaw, 2008). The R&D department focuses on generating innovations, developing product platforms, and standardizing modules. In addition to generating new ideas, the R&D department also focuses on adapting existing products to regional markets and customers (Simon *et al.*, 2008).

At the same time, overall efficiency goals require the R&D department to consider the effects of its decisions on the manufacturability of the products (e.g. the resultant manufacturing costs); however, the spatial and organizational separation of R&D and manufacturing tasks limits knowledge transfer that might facilitate this sort of consideration, which is necessary to improve manufacturability and reduce manufacturing costs (Birkinshaw and Gibson, 2004).

Within the archetype network, the R&D department explores new products and processes and transfers the results to the production plants. The production plants are responsible for producing the new products and exploiting the existing product portfolio. Each of the internationally distributed production plants interacts with the R&D department and translates R&D knowledge into manufacturing processes and specifications. Knowledge sharing within the archetype network depends on the location of the receiving plant. Usually, only a plant in the same region as the R&D department profits from strong personal ties with the R&D department. More distant plants have weaker personal ties and therefore have lower levels of absorptive capacity, which limits the efficiency of knowledge transfer between the R&D department and these plants.

From a process perspective, each of the plants has the responsibility of turning R&D knowledge into a prototype and to begin serial production based on subsequent improvements of the prototype. We assume that multiple plants produce the same products. Therefore, the costs associated with transferring R&D knowledge into a prototype and the subsequent improvements leading to the serial production of the new product have to be incurred at each plant.

3. A simple model for production ramp-up and serial production

We consider a firm that produces a certain product and has a choice between two distinct intra-firm network structures:

1. the lead factory concept, in which the R&D department works closely with the lead factory and transfers knowledge to the branch factories; and
2. an archetype network structure, in which the R&D department and the production plants are organizationally separated.

We assume that the production network consists of $n \geq 1$ different production plants.

In our analysis, we focus on knowledge transfer within an R&D and manufacturing network. Because companies not only have to invent or improve products within the

R&D department but also have to efficiently transfer generated knowledge to the production units, knowledge transfer is a central part of achieving a competitive advantage (Simon *et al.*, 2008). We therefore analyze the efficiency of knowledge transfer from exploration to exploitation by comparing the efficiency of knowledge transfer within the lead factory concept and the archetype network structure. We speak of an efficient knowledge transfer if it is feasible to transfer the relevant knowledge between units. Feasible in this context means that the transaction costs to transfer the knowledge are sufficiently low. Because knowledge transfer influences overall manufacturing costs, we compare the cost efficiency of both forms of organization.

In the lead factory concept, the prototype is constructed in the lead factory, whereas in the archetype network, the prototype is directly constructed in each manufacturing plant. The prototype is the last step in which R&D is involved before the first production series is run. Production of the prototype may be interpreted as the final "rehearsal." After the prototype has been produced, adaptations are eventually made to the product or process, depending on the experiences gained during the manufacturing of the prototype.

To make our model more tractable, we consider the development and production of a single product. This product is developed by the R&D department either with or without the collaboration of a lead factory and is then produced by one or more manufacturing units according to the following cost function:

$$C(q, x_b, x_s) = c_1(q) + c_2(x_b, x_s),$$

where $q > 0$ denotes the number of units that are produced and $x_b \geq 0$, $x_s \geq 0$ are choice variables controlled by the plants to optimally adapt their production process. The total manufacturing costs consist of two components:

(1) labor and material costs, $c_1(q)$; and

(2) ramp-up and learning costs, $c_2(x_b, x_s)$.

Labor and material costs are determined by a convex cost function $c_1(q)$ with $\partial c_1(q)/\partial q > 0$ and $\partial^2 c_1(q)/\partial q^2 \geq 0$.

Ramp-up and learning costs $c_2(x_b, x_s)$ appear until the production process is optimally adapted to all production requirements. As noted above, we distinguish between the basic and the specific dimensions of a production process P. The basic dimension describes new knowledge that can be used by all plant managers. The specific dimension refers to new knowledge that depends on the individual characteristics of the plant. The execution of the two dimensions of the production process has a different cost structure. We denote the costs associated with producing the product using basic and specific processes by p_b and p_s, respectively, and weight them according to:

$$P = \mu p_b + (1 - \mu)p_s,$$

where $\mu \in [0, 1]$ is the proportion of basic processes within the production process. We specify p_b and p_s as follows:

$$p_b = (\hat{\theta}_b - x_b)^2 \text{ and } \mathrm{p}_s = (\hat{\theta}_s - x_s)^2,$$

where $\hat{\theta}_b$ and $\hat{\theta}_s$ are random variables. Before the manufacturing of the prototype, each plant has only incomplete information about the costs associated with the production process. This uncertainty regarding the costs is modeled via the random variables $\hat{\theta}_b$

and $\hat{\theta}_s$, which are independent and continuously distributed with expected values given by $E[\theta_b] = \theta_b > 0$, $E[\theta_s] = \theta_s > 0$, and variances given by $Var[\theta_b] = \sigma_b^2 \in (0, \infty)$, $Var[\theta_s] = \sigma_s^2 \in (0, \infty)$. A higher expected value means that the production process potentially leads to higher costs if the process is not yet optimally adapted, whereas a higher variance reflects a higher uncertainty about the production process.

Each plant can change x_b and x_s to optimally configure and adapt its production process, contingent on the information about $\hat{\theta}_b$ and $\hat{\theta}_s$. To illustrate our specification of p_b and p_s, we depict them as functions of x_b and x_s in Figure 1.

The figure shows that $x_b = \hat{\theta}_b$ and $x_s = \hat{\theta}_s$ characterize the efficient configurations of the production process at which ramp-up and learning costs are minimized. These cost-minimizing configurations reflect the "steady-state phase" where learning ceases and costs reach a plateau level (Yelle, 1979). According to Yelle's (1979) "plateau model", costs decrease in the initial phase after which costs reach a "steady-state phase" where learning ceases. Many other researchers have observed and modeled this "plateau effect" (Baloff, 1971; Hall and Howell, 1985; Muth, 1986; Stratman *et al.*, 2004). It is important to mention that the plateau effect may not last in dynamic environments because technical/technological progress can change the process conditions continuously.

Similar to Cabral and Riordan (1997), who allow that the marginal cost to eventually reach zero as production experience increases, we normalize the plateau level to zero, that is, $E[c_2(\hat{\theta}_b, \hat{\theta}_s)] = 0$. Qualitatively, the results would not change if we introduced a plateau level (i.e. a constant) larger than zero. However, in this case, the notation would become cumbersome without adding any new insights.

It should be noted that these cost-minimizing configurations can only be implemented if the plant has full information about the production process. We assume that each plant obtains full information about the process through the manufacturing of a prototype. In this case, the plant can optimally adapt its subsequent production process by setting $x_b = \hat{\theta}_b$ and $x_s = \hat{\theta}_s$ such that $E[c_2] = 0$.

With incomplete information about the production process, each plant only knows the distributions of $\hat{\theta}_b$ and $\hat{\theta}_s$. In this case, however, each plant can form expectations $E[p_b]$ and $E[p_s]$ about the associated costs such that the expectations $E[c_2(x_b, x_s)]$ about total ramp-up and learning costs are given by:

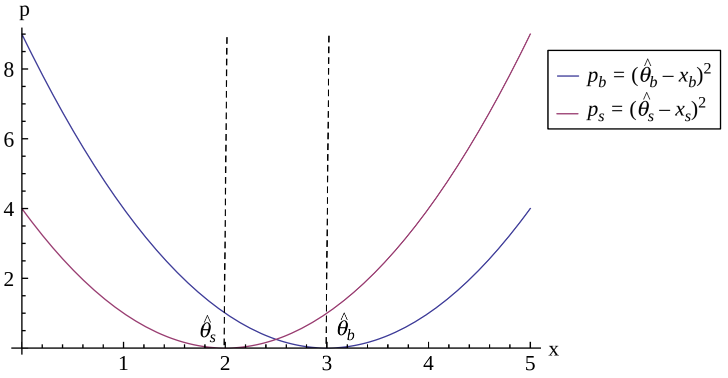

Figure 1.
Costs associated with basic and specific processes

$$E[c_2(x_b, x_s)] = \mu E[(\hat{\theta}_b - x_b)^2] + (1 - \mu)E[(\hat{\theta}_s - x_s)^2].$$

Whether knowledge about the basic and the specific processes (after the production of the prototype) can be efficiently transferred from the lead factory to the manufacturing plants depends on the heterogeneity between the plants. We distinguish two scenarios. In Scenario 1, we assume that the heterogeneity between the production plants is sufficiently low, such that knowledge about the basic and specific processes can be efficiently transferred from the lead factory to each production plant. In Scenario 2, we assume that the heterogeneity between the production plants reaches a level such that only knowledge about the basic processes can be efficiently transferred from the lead factory to the plants. Knowledge regarding specific processes cannot be efficiently transferred to the plants. A third scenario is imaginable in which the heterogeneity between production plants is too high such that no relevant knowledge can be efficiently transferred to the production plants. However, it is obvious that the archetype network structure is always more efficient than the lead factory concept in this scenario because the lead factory's production of the prototype creates additional costs without providing additional benefits.

Finally, if relevant knowledge about the production process is efficiently transferred to the plants, there are (one-time) adaptation costs in each plant, which are given by $k_b > 0$ for basic processes and $k_s > 0$ for specific processes. One-time adaptation costs reflect the efforts of a plant to adapt to new circumstances (e.g. investments in new equipment, technologies, and training and efforts in data handling). We proceed by analyzing the lead factory concept in the next section and the archetype network structure in Section 3.2. We compare both network structures in Section 4.

3.1 Lead factory concept

In this section, we consider the lead factory concept and assume the following timing of the production process:

- *Stage 1.* The prototype is designed in cooperation with the R&D department and is manufactured in the lead factory. During this phase, the lead factory generates knowledge about the basic and specific processes.
- *Stage 2.* At this stage, we differentiate two generic scenarios that reflect the heterogeneity of the production plants and the resulting efficiency of knowledge transfer from the lead factory to the various plants. Using the knowledge generated in Stage 1, each plant optimally adapts the basic and specific processes of its production process, after which serial production begins.

3.1.1 Stage 1. In Stage 1, after receiving the process recipe from the R&D department, the lead factory still has incomplete information about the production process; in other words, it only knows the distributions of $\hat{\theta}_b$ and $\hat{\theta}_s$ but not the realizations of the random variables. To manufacture the prototype, the lead factory determines the optimal configuration of the basic and specific processes by minimizing the expected costs $E[c_2(x_b, x_s)]$ of the second cost component. Formally, the lead factory solves the following minimization problem:

$$\min_{(x_b,x_s)} E[c_2(x_b, x_s)] = \min_{(x_b,x_s)} \{\mu E[(\hat{\theta}_b - x_b)^2] + (1 - \mu)E[(\hat{\theta}_s - x_s)^2]\}.$$

To minimize the expected costs of the basic processes under incomplete information, the lead factory solves $\partial E[c_2]/\partial x_b = 2\mu E[(\hat{\theta}_b - x_b)] = 0$ and therefore will set $x_b = \theta_b$ such that $E[(\hat{\theta}_b - \theta_b)^2] = \sigma_b^2$. Similarly, to minimize the expected costs of the specific processes, the lead factory solves $\partial E[c_2]/\partial x_s = 2(1-\mu)E[(\hat{\theta}_s - x_s)] = 0$ and therefore will set $x_s = \theta_s$ such that $E[(\hat{\theta}_s - \theta_s)^2] = \sigma_s^2$. That is, with incomplete information about the production process, the plant minimizes expected ramp-up and learning costs $E[c_2]$ by implementing the expected values of the random variables $\hat{\theta}_b$ and $\hat{\theta}_s$ As a result, the expected costs of the second cost component are given in this case by $E[c_2(\theta_b, \theta_s)] = \mu\sigma_b^2 + (1-\mu)\sigma_s^2$. It follows that the manufacturing costs C_P for the prototype in the lead factory amount to:

$$C_P = c_1(1) + \mu\sigma_b^2 + (1-\mu)\sigma_s^2,$$

where $c_1(1)$ denotes the material costs of the prototype and $\mu\sigma_b^2 + (1-\mu)\sigma_s^2$ are the expected ramp-up and learning costs.

We assume that the lead factory generates the knowledge about the basic and specific processes during the design and implementation of the manufacturing processes of the prototype. In other words, the lead factory learns the realizations of the random variables $\hat{\theta}_b$ and $\hat{\theta}_s$. Whether this knowledge can be efficiently transferred to the production plants depends on the heterogeneity of these plants. As noted above, we distinguish two scenarios of production plant heterogeneity: low and high.

3.1.2 Stage 2.

Scenario 1. Low heterogeneity. In this scenario, the heterogeneity between the production plants is sufficiently low, and knowledge about the basic and specific processes can be efficiently transferred from the lead factory to each production plant after the lead factory has generated it. Through the knowledge transfer, one-time adaptation costs of both basic and the specific processes, which are given by k_b and k_s, must be incurred in each production plant. Once the manufacturing units have absorbed knowledge about the basic and specific processes from the lead factory, each production plant will optimally adapt its production process to both dimensions. After the successful adaptation, the second cost component reaches the plateau level, that is, $E[c_2] = 0$. After successful adaptation, serial production takes place in each plant.

In Scenario 1, the firm's total manufacturing costs for producing units in each plant are thus given by:

$$C^1_{LF} = \underbrace{c_1(1) + \mu\sigma_b^2 + (1-\mu)\sigma_s^2}_{\text{costs for prototype in LF (stage 1)}} + n \cdot [\underbrace{k_b + k_s + c_1(q)}_{\text{total costs for } q \text{ units in each plant (stage 2)}}].$$

With $C_P = c_1(1) + \mu\sigma_b^2 + (1-\mu)\sigma_s^2$, total manufacturing costs in Scenario 1 can be written as $C^1_{LF} = C_P + n[k_b + k_s + c_1(q)]$.

Scenario 2. High heterogeneity. In this scenario, the heterogeneity between the production plants is high, and only knowledge about the basic processes can be efficiently transferred from the lead factory to the plants. Knowledge regarding the specific processes cannot be efficiently transferred to the production units. Consequently, the plants can optimally adapt their production process only with respect to the basic processes, resulting in adaptation costs of k_b. In this case, only the costs associated with the basic processes reach the plateau level (i.e. $E[(\hat{\theta}_b - x_b)^2] = 0$), whereas the plants still have incomplete information about the specific processes, yielding expected costs of the second cost component larger than zero (i.e. $E[c_2] = (1 - \mu)E[(\hat{\theta}_s - x_s)^2] > 0$). Because of the incomplete knowledge transfer, the plants do not have enough information to immediately begin serial production but must instead produce their own prototype to generate knowledge suited to the specific processes of their production process.

To manufacture the plant-specific prototype, each plant determines the optimal configuration for the specific processes by minimizing the expected costs associated with the specific processes, that is, $\min_{x_s} E[(\hat{\theta}_s - x_s)^2]$. We derive that each plant will set $x_s = \theta_s$ such that $E[(\hat{\theta}_s - \theta_s)^2 = \sigma_s^2$. As a result, the expected costs of the second cost component are given by $E[c_2] = (1 - \mu)\sigma_s^2$ yielding the following production costs of the plant-specific prototype:

$$\hat{C}_P = c_1(1) + (1 - \mu)\sigma_s^2,$$

where $c_1(1)$ denotes the material costs for the plant-specific prototype and $(1 - \mu)\sigma_s^2$ are the expected ramp-up and learning costs.

We refer to $\hat{C}_P$ as the "reduced" manufacturing costs for the plant-specific prototype because they are lower than those associated with the first prototype produced at the lead factory (i.e. $\hat{C}_P < C_P$). This reduction occurs because knowledge regarding the basic dimension can be transferred from the lead factory to the plant.

After the production of its plant-specific prototype, each production unit has generated knowledge about the specific processes of its production process, such that it is able to fully adapt its production process with respect to both processes. As a result, the second cost component reaches the plateau level (i.e. $E[c_2] = 0$). Consequently, the costs of serially producing q units of the respective product will be given by $c_1(q)$.

In Scenario 2, the total costs of producing q units in each plant are thus given by:

$$C_{LF}^2 = \underbrace{c_1(1) + \mu\sigma_b^2 + (1 - \mu)\sigma_s^2}_{\text{costs for prototype in LF (stage 1)}} + n \cdot [\underbrace{k_b + c_1 + (1 - \mu)\sigma_s^2 + c_1(q)}_{\text{total costs for } q \text{ units in each plant (stage 2)}}].$$

With $C_P = c_1(1) + \mu\sigma_b^2 + (1 - \mu)\sigma_s^2$ and $\hat{C}_P = c_1(1) + (1 - \mu)\sigma_s^2$, the total manufacturing costs in Scenario 2 can be written as $C_{LF}^2 = C_P + n[k_b + \hat{C}_P + c_1(q)]$.

3.2 The archetype network structure

In this section, we model the archetype network structure and assume the following timing of the production process:

- *Stage 1.* Each of the n production plants manufactures its own prototype, such that knowledge about basic and specific processes is directly generated in each plant; thus, no (or very low) adaptation costs are incurred.
- *Stage 2.* The serial production of the product occurs in each production plant.

3.2.1 Stage 1. In Stage 1, each production plant manufactures its own prototype. To minimize the expected costs $E[c_2]$ of the second cost component, each production plant sets $(x_b, x_s) = (\theta_b, \theta_s)$ in Stage 1, such that $E[c_2] = \mu\sigma_b^2 + (1 - \mu)\sigma_s^2$. Note that the logic behind this behavior is similar to the Stage 1 behavior of the lead factory. It follows that the manufacturing costs of the prototype in each production plant are given by $C_P = C_1(1) + \mu\sigma_b^2 + (1 - \mu)\sigma_s^2$.

After the production of the prototype, each plant has generated knowledge about the basic and specific processes. Therefore, in the subsequent production, each plant can optimally adapt its production process with respect to both types of processes.

3.2.2 Stage 2. In Stage 2, the production process runs "smoothly" (i.e. it is now optimally adapted to basic and specific processes, such that the expected costs of the second cost component reach a plateau such that $E[c_2] = 0$). It follows that the manufacturing costs for q units are subsequently given by $c_1(q)$. Thus, the firm's total manufacturing costs for producing q units in each plant yield:

$$C_{AN} = n \cdot \left[\underbrace{c_1(1) + \mu\sigma_b^2 + (1-\mu)\sigma_s^2}_{\text{costs for prototype (stage 1)}} + \underbrace{c_1(q)}_{\text{total costs for } q \text{ units (stage 2)}} \right].$$

With $C_P = c_1(1) + \mu\sigma_b^2 + (1-\mu)\sigma_s^2$ the total manufacturing costs can be written as $C_{AN} = n \cdot [C_P + c_1(q)]$.

4. Results

In this section, we compare the total manufacturing costs C_{LF}^1 and C_{LF}^2 for producing q units under the lead factory concept to the total manufacturing costs C_{AN} in the archetype network structure for each of the two scenarios. We establish the following proposition:

Proposition 1. The lead factory concept is more profitable than the archetype network structure if (i) $n \cdot (k_b + k_s) < (n-1) \cdot C_P$ (Scenario 1) or (ii) $n \cdot (k_b + \hat{C}_P) < (n-1) \cdot C_P$ (Scenario 2).

Part (i) of the proposition shows that in Scenario 1, the lead factory concept is more (less) profitable than the archetype network structure if n-times the combined adaptation costs, $k_b + k_s$, of the basic and specific processes are lower (higher) than $(n-1)$-times the manufacturing costs C_P of the prototype.

Remember that the prototype has to be manufactured in the archetype network structure in each production plant, whereas in the lead factory concept, it is only manufactured in the lead factory. Moreover, in Scenario 1, knowledge about the basic and specific processes can be efficiently transferred from the lead factory to the production units, which can then optimally adapt their production process (after adaptation costs of $k_b + k_s$).

Thus, *ceteris paribus*, the relative profitability of the lead factory concept depends on the following critical factors:

- A higher number n of production plants: this is intuitively clear because the manufacturing costs of the prototype occur in each of the n production plants under the archetype network structure, whereas in the lead factory concept, these costs are incurred once. Because multiple plants profit from the prototyping efforts within the lead factory, the concept reduces the production costs of the prototype by a factor of $(n-1)$. If there are $n = n'$ production plants with $n' \equiv (C_P/(C_P - (k_b + k_s)))$, then both network structures are equally profitable. If $n > n'$, then the lead factory concept is more profitable. Lower adaptation costs for either dimension of the production process (or, equivalently, higher manufacturing costs of the prototype) lead to a lower threshold number n'.

- Lower adaptation costs, k_b and k_s, for the basic and specific processes, respectively: remember that in the lead factory concept, each manufacturing unit incurs adaptation costs to optimally adapt the production process with respect to each dimension in every production unit. As the cost of each kind of adaptation decreases, the lead factory concept becomes more profitable.
- Higher manufacturing costs C_P of the prototype: because the prototype has to be manufactured in every production unit when using the archetype network structure and only once when using the lead factory concept, the profitability of the lead factory concept increases with higher C_P.

Part (ii) of *Proposition 1* shows that in Scenario 2, the lead factory concept is more profitable than the archetype network if $n \cdot (k_b + \hat{C}_P) \leq (n-1)C_P$. The archetype network is more profitable than the lead factory concept if the inequality is inverted. The left-hand side of the inequality represents the adaptation costs k_b for the basic processes in each plant and the (reduced) manufacturing costs $\hat{C}_P$ for a further prototype in each plant (if the production process is only optimally adapted regarding the basic processes) times the number n of production plants. If these costs are lower (higher) than $(n-1)$-times the (full) manufacturing costs C_P for a prototype, then the lead factory concept is more (less) profitable.

Thus, *ceteris paribus*, the following factors favor the lead factory over the archetype network structure:

- A higher number n of production plants, lower adaptation costs k_b for the basic processes, and higher (full) manufacturing costs C_P for the prototype: these factors have effects that are similar to those observed in Scenario 1. As in Scenario 1, we compute the threshold number n'' of production plants for which both networks are equivalently profitable as $n'' \equiv (C_P/(C_P - (k_b + \hat{C}_P)))$. If $n > n''$, then the lead factory is more profitable than the archetype network structure. Higher (full) manufacturing costs for the prototype (or, equivalently, lower adaptation costs with respect to the basic processes and lower manufacturing costs for the second prototype) result in a lower threshold n'' for which both networks are equivalently profitable.
- Lower manufacturing costs $\hat{C}_P$ for the second prototype (produced at a production plant) if knowledge about basic processes can be efficiently transferred to the production units: even though a further prototype has to be built in Stage 2 in each production plant using the lead factory concept, manufacturing costs can be reduced due to the available knowledge regarding basic processes; however, this is not possible using the archetype network structure, as each plant has to incur the full costs C_P of producing the prototype.
- A lower specificity of the production process, i.e. a higher μ: note that the manufacturing costs $\hat{C}_P = c_1(1) + (1-\mu)\sigma_s^2$ decrease with the relative importance of the basic processes, which is given by the weight μ. If the production process is primarily characterized by basic processes, then it is clear that knowledge about basic processes transferred from the lead factory to the plants is more valuable because it contains useful information about how to optimally adapt the production process. It follows that a high μ also renders the lead factory concept more profitable than the archetype network structure.

The lead factory concept is more profitable in Scenario 1 than in Scenario 2 because the adaptation costs k_s with respect to the specific processes are lower than the manufacturing costs $\hat{C}_P$ of the prototype. In other words, the lead factory concept has advantages over the archetype network if the heterogeneity between the production plants is low.

5. Discussion and conclusion

We have analyzed two distinct network structures to understand which concept is the most profitable. Based on our analytical model, we isolate the following factors that render the lead factory concept more profitable than the archetype network:

- a high number of production plants;
- low adaptation costs for the basic and specific processes;
- high manufacturing costs for the prototype if knowledge about basic and specific processes can be efficiently transferred;
- low manufacturing costs for the second prototype (produced at a production plant) if only knowledge about the basic processes can be efficiently transferred; and
- the production process is characterized through a low specificity (i.e. the relative importance of the basic processes is high).

Although the advantages of a lead factory concept are intuitively understandable, not every company can profit from the intermediary activities. Looking at the factors that render a lead factory concept profitable highlights which companies are not suitable for the lead factory concept. The following discussion critically reflects on the five factors found.

The first factor derived from our model that renders a lead factory more profitable than an archetype network is the number of the production plants within the network. It is obviously desirable to have a greater number of production plants that can profit from knowledge transferred from an intermediary. This requires that the plants are producing similar products. However, many companies face another situation. To profit from economies of scale and scope, companies can decide to implement a world factory (Abele *et al.*, 2008). Each plant is clearly specialized in the production of one product type; for example, the Korean electronics group Samsung has concentrated all of its front-end factories for semiconductor chips in South Korea, achieving highly beneficial synergies from pooling its manufacturing capacity and staff (Abele *et al.*, 2008). We therefore conclude that companies must align the focus of the plants to profit from the lead factory concept.

The second factor that renders a lead factory advantageous reveals the importance of low one-time adaptation costs for the basic and specific processes. High adaptation costs are a common disadvantage of an archetype network structure because they incur in each plant. Within this structure, R&D employees have to work with multiple plants that are often distributed across the globe. Therefore, it is possible that knowledge about each of the individual specifications of the production processes and equipment is not as good as that obtained using the lead factory concept. However, to avoid the investments resulting from the intermediary activities of a lead factory, companies try to ameliorate this problem with the concept of "design for manufacture and assembly" (Boothroyd *et al.*, 2001). Using this concept, the goal is to design the product according to manufacturing requirements. To achieve this goal, the manufacturing employees are included in the development process as early as possible. One consequence of this strategy is that plants have to be assigned to a particular product line at an early stage. Following the requirements of this concept allows companies without a lead factory to minimize the disadvantage of higher adaptation costs during the production processes. We therefore conclude that instead of implementing the lead factory concept, companies with an archetype network could also profit from implementing the concept of "design for manufacture and assembly".

The third factor in favor of the lead factory concept is high manufacturing costs for the prototype if knowledge about the basic and specific processes can be efficiently transferred from the lead factory to the plants. The manufacturing costs for a prototype vary widely. For example, in the case of building an alternator, the prototype is often included in the first product to be sold because the labor and material costs can be extremely high; however, industries with lower labor and material costs (e.g. the production of printer boards, drilling machines, or other consumer goods) have different production processes. The manufacturing costs for a prototype differ between industries. Therefore, the suitability of the lead factory concept also depends on the company's industry.

The fourth factor highlights the importance of low manufacturing costs for the second prototype if knowledge about the basic processes can be efficiently transferred from the lead factory to the plants. The concept of the lead factory is intriguing because the experience gained during the production of the prototype in the lead factory can be directly shared and discussed with the R&D and manufacturing departments on-site. If a second prototype must be produced at production sites, additional costs occur. The suitability of the lead factory concept thus depends on how much the receiving plants of the lead factory concept can profit from receiving process descriptions of the basic processes.

Finally, the lead factory concept becomes more profitable as the specificity of a production process decreases; however, many successful companies from developed countries often follow a strategy of differentiation. Accordingly, their manufacturing processes are likely to be highly specific. This specificity is primarily due to the fact that basic processes are much easier to duplicate than specific processes. The analysis developed herein demonstrates that the lead factory concept becomes relatively more profitable as specificity decreases. This result implies that the relative efficiency of the lead factory concept can be improved as the percentage of the basic processes needed to produce a product increases; however, an ambition toward this simplicity could negatively affect unique selling positions. Manufacturing companies from developed countries are often known for their unique capabilities, such as the ability to fulfill customer needs that are bound to specific processes, which often put them at a competitive advantage. The ultimate result of reducing the degree of specific processes has to be carefully analyzed.

In summary, our study can be seen as a first attempt to highlight the conditions under which the lead factory concept is advantageous. However, the discussion of the five factors that render the lead factory more profitable than the archetype network shows that not all manufacturing networks can profit from this concept. These results demonstrate that the lead factory concept has a large potential for achieving a competitive advantage. That being said, the factors that influence the potential of the lead factory concept have to be carefully considered. From a theoretical perspective, our analysis clarifies the potential of the lead factory concept; however, we caution readers to consider the factors that render the lead factory concept more or less profitable. As discussed above, many companies must consider different factors that would make it unwise to implement a lead factory. Additionally, the analysis shows that multiple factors influence the profitability of the lead factory concept. Decisions focusing on only one or two of these factors discussed could lead to a suboptimal result.

From a managerial perspective, these results highlight the need to analyze the network structure and to align the structure with contingency factors. With an aim to improve knowledge transfer, each company must determine whether the specific contingencies that render a lead factory concept more profitable than the archetype network structure are present.

A promising avenue for further research in this area would be to test the derived factors empirically in order to generate further insights into the suitability of the lead factory concept. Particularly, it would be interesting to test the identified factors such as plant number, adaptation costs, manufacturing costs of the prototypes and specificity of the production process empirically in order to understand how network performance, based on the two distinct network structures, is influenced. Another promising expansion would be to analyze how contingency factors such as industry type, market dynamism or ownership influences the results. Moreover, it would be interesting to generalize our findings by modeling competition and by allowing for the possibility of producing more than one product. Finally, our model could be extended to multiple periods. Introducing temporal dynamics may yield valuable insights into the inter-temporal benefits of the lead factory concept.

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