

Sparking Manufacturing Innovation: How Temporary Interplant Assignments Increase Employee Idea Values

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Abstract

Shop-floor employees play a key role in manufacturing innovation. In some companies, up to 75% of all productivity gains are the result of bottom-up employee ideas. In this paper, we examine how employee interplant assignments—short problem-solving jobs at other manufacturing plants within the same firm—influence employee-driven manufacturing innovation. Using unique idea-level data from a large European car parts manufacturer, we show that interplant assignments significantly increase the value of employees' improvement ideas due to the short-term transfer of production knowledge and long-term employee learning. Both effects are amplified by assignments to plants that have high functional overlap (i.e., plants producing similar products using similar processes and machinery). One implication is that, for the purpose of employee-driven manufacturing innovation, assignments between peripheral plants with high functional overlap can be more effective than assignments to and from central plants. These findings are robust to several econometric tests. Our study provides novel and detailed empirical evidence of manufacturing innovation, and goes beyond previous research on the learning curve (learning by doing) by investigating how interplant assignments affect the value of employees' improvement ideas (learning by moving).

1 Introduction

Continuous process and product innovation has become a primary source of competitive advantage in the manufacturing industry. To make a profit, many firms today rely on their ability to repeatedly push performance boundaries by making small adjustments to products, processes, and machinery. While research and development (R&D) plays a prominent role in manufacturing innovation, many improvements are created by front-line employees with deep specialist production knowledge. Across industries, such employee improvements have been shown to create as much as 75% of total annual factor productivity gains, even in already well-performing factories (Sting & Loch 2016). Many companies renowned for front-line innovation—including BMW, Toyota, Kellogg's, Lantech, and Chevron (Loch et al. 2010; Power 2011)—operate large manufacturing networks in which shop-floor employees are frequently sent to other plants to support the resolution of small production issues.

Although such temporary interplant assignments are common,¹ we only have a limited understanding of their implications for front-line innovation. Building on prior studies of knowledge transfer (Ferdows 2006; Siemsen et al. 2008; Lang et al. 2014; Gray et al. 2015), employee learning (Tyre & von Hippel 1997; Narayanan et al. 2009; KC & Staats 2012; Staats & Gino 2012), and plant typologies (Ferdows 1997), we therefore investigate how interplant assignments influence employee-driven manufacturing innovation.

To address this topic, we employ a unique data set from a large European car parts manufacturer. The data include all the process and product improvement ideas submitted by manufacturing employees between 2006 and 2010. During this period, 21,131 ideas generated more than €800 million of production-related cost savings (about 8% of the business unit's revenue). Unlike patent-based studies of employee mobility in R&D (e.g., Almeida & Kogut 1999), these data allow us to study shop-floor innovation rather than R&D-driven innovation and avoid limitations of patent data.² By observing assignments within the same corporate environment we are also controlling for potentially confounding heterogeneity between companies. In addition, we use fixed effects, dynamic control variables, coarsened exact matching (Iacus et al. 2011), and Monte Carlo simulations to test our hypotheses while controlling for several potential confounders.

We find that interplant assignments increase front-line innovation in two distinct ways. During and shortly after assignments, employees submit more valuable improvement ideas, which we argue is due to the transfer of production know-how between their home plants and the assignments' destination plants. This short-term effect subsides quickly once all opportunities for knowledge transfer have been exhausted. It is followed by a learning effect that materialises in the months after an employee's return and that increases idea values in the long term. The knowledge transfer effect is larger in the short term, but the learning effect is perpetual: it does not diminish during our four-year study period. We also establish that both effects are stronger for assignments between plants that have high functional overlap—in other words, plants that share similar processes, machinery, and products. We conclude with a range of boundary conditions that firms can use to implement assignment programmes.

This study makes several contributions to the operations management literature. We address calls for “more research from a perspective inside the production function” (Ferdows 2006, p.2) by investigating the role of interplant assignments in employee-driven manufacturing innovation. In doing so, we link the literature on flexible and distributed work *within* firms that has focused on individual worker productivity (e.g., Staats & Gino 2012; Bonet & Salvador 2017) to the literature on employee mobility *between* firms which has emphasised organisational innovation outcomes (e.g., Almeida & Kogut 1999; Song et al. 2003). Our research combines both perspectives by studying the effect of

¹ For instance, in the European Union (EU), 2.05 million employees were temporarily assigned by their employer to work in another EU member state in 2015, 25% of whom worked in manufacturing. From 2010 to 2015 intra-EU assignments grew by 41% (European Commission 2016).

² Very innovative firms, for example, may strategically refrain from patenting in competition (cf. Mihm et al. 2015).

interplant assignments on the innovation performance of individual manufacturing employees. While research in economics has questioned the ability of manufacturing employees to embody and transfer production know-how (Levitt et al. 2013), we provide evidence that manufacturing employees on interplant assignments are an important conduit for such knowledge. We also extend prior studies on employee learning (e.g., Narayanan et al. 2009; Staats & Gino 2012) by showing how interplant assignments stimulate conceptual learning in manufacturing employees. In contrast to research that found production knowledge to decay quickly (Argote et al. 1990; Epple et al. 1996), our study reveals that conceptual learning boosts employee contributions to manufacturing innovation for several years. Finally, while prior research has emphasised the role of central plants in manufacturing innovation—i.e., plants that take the lead in process and product development (Ferdows 1997; Lapré & Van Wassenhove 2001; Lang et al. 2014)—we find that assignments between peripheral plants—i.e., those that follow established processes—can be better suited to stimulate employee innovation when there is high functional overlap between them.

The rest of our paper proceeds as follows. The literature is reviewed in §2, where we also develop and formally state four hypotheses. Our data and methods are described in §3, and §4 presents the results. We conclude in §5 with a summary discussion and some suggestions for future research.

2 Theory and Hypotheses

2.1 Literature Review

The literature on employee mobility has predominantly studied the interfirm movements of knowledge workers (e.g., managers and R&D staff) and the resulting cross-organisational transfers of technologies, resources, and business relations (e.g., Almeida & Kogut 1999; Song et al. 2003; Franco & Filson 2006; Mawdsley & Somaya 2016). A related stream of research has also studied the role of internal mobility in distributed R&D organisations (Singh 2008; Lahiri 2010; Choudhury 2017). Yet at the individual level it remains unclear how moves affect employees' innovation output; in fact, several studies have found that employees perform worse at their jobs after moving (Groysberg et al. 2008; Dokko et al. 2009; Raffiee & Byun 2020). Research on how manufacturing and service employees learn from different work settings has similarly focused on worker productivity. Huckman and Pisano (2006) find that surgeons' learning does not fully transfer across hospitals, and KC and Staats (2012) show that this partly depends on the type of experience accumulated (focal vs. related). Within firms, distributed work has often been associated with reduced performance (see MacDuffie 2007), although remote supervision can also protect workers from overzealous managers (Bonet & Salvador 2017). When it comes to the execution of different tasks, specialisation increases performance more than variety, but variety supports learning through a range of second-order mechanisms (e.g., learning to learn) (Boh et al. 2007; Narayanan et al. 2009; KC & Staats 2012; Staats & Gino 2012; Clark et al. 2013). Beyond

worker productivity, however, the implications of interplant assignments for front-line innovation are not well understood. This is where we aim to contribute.

Manufacturing innovation is driven by the two interrelated processes of operational and conceptual learning (Kim 1993; Mukherjee et al. 1998). On the one hand, operational learning is the acquisition of production know-*how*: procedural knowledge about the efficient execution of manufacturing tasks, such as how to configure a machine or which alloy to use for welding (Kogut & Zander 1992; Garud 1997; Ferdows 2006). On the other hand, conceptual learning amounts to the acquisition of production know-*why*, or causal knowledge, that comprises abstract “principles and theories underlying the functioning of a technical system” (Garud 1997, p. 86).

There are arguments to be made that interplant assignments affect both learning processes. During and shortly after assignments, the exchange of employees between plants may contribute to operational learning by facilitating the transfer of production know-how. The ability to transfer production know-how internally is an important source of competitive advantage for manufacturing firms (Adler 1990; Kogut & Zander 1992; Grant 1996a; Grant 1996b). Prior research has examined knowledge transfer between R&D and manufacturing (Adler 1995; Ettlie 1995; Hatch & Mowery 1998; Gerwin & Barrowman 2002; Gray et al. 2015), between and within plants (Argote & Epplé 1990; Pil & MacDuffie 1999; Lapré & Van Wassenhove 2001; Ferdows 2006; Siemsen et al. 2007; Siemsen et al. 2008; Lang et al. 2014), and between supply chain functions (e.g., Pagell 2004; Flynn et al. 2010). Especially knowledge sharing between plants can improve firm performance by diffusing the productivity improvements that individual plants have achieved through their path-dependent (Kogut & Zander 1992) and context-dependent (Argote & Miron-Spektor 2011) accumulation of experience (Adler 1990; Argote & Epplé 1990). However, several studies have noted the difficulty of transferring knowledge *after* plants have begun production (Adler 1990; Argote et al. 1990; Lapré & Van Wassenhove 2001). Whereas some scholars have claimed that employees are a good conduit for knowledge transfer (Darr et al. 1995; Ferdows 2006; Argote & Fahrenkopf 2016), others have found no evidence of knowledge transfer through manufacturing employees (Epplé et al. 1996; Levitt et al. 2013). As Levitt et al. note: “knowledge obtained through learning by doing ... is by and large not retained by the plant’s workers” (p.679). Thus, our first research question is whether—and, if so, how—employees on interplant assignments contribute to operational learning through the transfer of production know-how between plants.

Aside from facilitating knowledge transfer, interplant assignments may also contribute to conceptual learning by stimulating the creation of production know-why. There is evidence that moving between contexts supports abstraction and theory-building in individuals (Reber 1989). This kind of learning yields a deeper understanding of how causes (here, process and product modifications) relate to effects (productivity improvements), which is particularly relevant in manufacturing contexts (Tyre & von Hippel 1997; Lapré et al. 2000). Extant research has examined the effect of *task* and *customer* variety on individual worker productivity (Narayanan et al. 2009; KC & Staats 2012; Staats & Gino

2012; Clark et al. 2013), but we are not aware of any studies offering evidence that working in a variety of *plants* stimulates conceptual learning—much less any evidence concerning how employees' innovation performance would be thereby affected. This lacuna motivates our second research question.

Because modern manufacturing networks usually comprise several types of plants, such as lead and server plants (Ferdows 1997), a salient question is whether assignments between certain plant types contribute more to manufacturing innovation than do those between other types. The focus of the existing literature has been on the transfer of knowledge from central plants (also referred to as “lead plants”), which typically adopt new technologies first, to peripheral plants (such as “server” or “source plants”), which usually implement technologies later and may learn from the experiences of central plants (Lapr e & Van Wassenhove 2001; Vereecke et al. 2006; Lang et al. 2014). We may expect similar results in the case of interplant assignments, such that employees who come from central plants and are assigned to peripheral plants transfer the most knowledge and that employees who come from peripheral plants and are assigned to central plants learn the most. That said, prior research has shown that successful knowledge transfer and learning requires some degree of similarity between the two environments (see e.g. Darr & Kurtzberg 2000; Narayanan et al. 2009; Egelman et al. 2017). Against the backdrop of this tension, we investigate how the functional overlap between plants—the similarity of processes, machinery, and products—influences how interplant assignments affect both operational and conceptual learning.

2.2 Operational Learning

We begin by discussing how interplant assignments affect operational learning through the transfer of production know-how between the employee's home plant and the assignment's destination plant. In many settings, moving employees between organisational units is an effective way to transfer knowledge, because employees can transfer both tacit and codified knowledge as well as adapt knowledge to the destination unit's specific circumstances (Argote & Fahrenkopf 2016). Interplant assignments further facilitate knowledge transfer by involving employees in the resolution of small production problems at the destination plant. During the problem-solving process, employees interact with local staff, inspect processes and machinery, and iteratively modify the production setup to isolate the issue and develop a solution. This extensive involvement increases visiting employees' embeddedness in the destination plant, which has two chief implications for their ability to transfer knowledge (Wang 2015; Kolympiris et al. 2019). First, it exposes them to production know-how embedded in the destination plant's staff, processes, and machinery (Grohsjean & Kryscynski 2018). As a result, visiting employees become more aware of pre-existing knowledge and are better able to recognise opportunities for knowledge transfer. Second, more than a passive plant visit, assignments create trust and familiarity between visiting employees and local staff, as both parties work together to resolve the production problem and, in so doing, further expand visitors' access to the plant's knowledge repositories (Levin & Cross 2004; Hinds & Cramton 2014).

Thus interplant assignments create an environment conducive to the employee-driven transfer of knowledge. Note that knowledge transfer need not occur only in the direction of the destination plant; it may occur also in the opposite direction. Thorough exposure to the destination plant's production know-how likely also reveals information about which the employee's home plant is unaware.³ Since the transfer and implementation of new production know-how tends to increase productivity (Adler 1990; Kogut & Zander 1992; Grant 1996a; Grant 1996b), we expect increases also in employee-driven manufacturing innovation—as measured by the value of employees' improvement ideas—during and shortly after interplant assignments. Formally, we state our first hypothesis as follows.

HYPOTHESIS 1 (H1). *The value of employees' improvement ideas increases during and shortly after interplant assignments.*

For production know-how from one plant to be applicable at another plant, the plants' processes, machinery, and products cannot differ by too much (Szulanski 1996; Garud 1997; Argote & Fahrenkopf 2016). Several studies have illustrated the importance of this required *functional overlap* for knowledge transfer. Egelman et al. (2017) observe knowledge transfer between overlapping generations of the same product (similar processes and machinery) but not between different product families (different processes and machinery). Likewise, Levitt et al. (2013) and Benkard (2000) find incomplete knowledge transfer between different car and airplane generations, respectively. Huckman and Pisano (2006) as well as KC and Staats (2012) report related results in the healthcare sector and reason that asset-specific knowledge is more difficult to transfer. Absent functional overlap, communication may also become more difficult because the local staff have different background knowledge and use a different technical lexicon (Carlile 2004). So when processes, machinery, and/or products are too different, one plant's know-how might not be applicable or communicable to another plant; in that case, knowledge transfer will be limited. These considerations lead to our next hypothesis.

HYPOTHESIS 2 (H2). *During and shortly after interplant assignments, the value of employees' improvement ideas increases more if there is high functional overlap between the plants.*

2.3 Conceptual Learning

We now consider how interplant assignments can lead to conceptual learning. While at the destination plant, employees are exposed to new production know-how—for instance, different machine configurations or input materials. On the one hand, this creates opportunities for knowledge transfer (as we have discussed in the previous section). On the other hand, new production know-how precipitates conceptual learning. At its heart, production know-how represents information on how a set of inputs is transformed into outputs. Observing different input–output relations in a manufacturing environment

³ Bidirectional flows of knowledge have also been documented for employee mobility between firms (Corredoira & Rosenkopf 2010; Kim & Steensma 2017; Kolympiris et al. 2019).

enables employees to build a causal understanding of the underlying principles of the production process—so-called production know-why (Kim 1993; Mukherjee et al. 1998). A core part of this process is the cumulative synthesis of observations from different contexts (in this case, the two plants) that allows employees to identify critical covariations between the contexts and hence to formalise the underlying structural relationships (Reber 1989; Garud 1997). So by exposing employees to production know-how from different contexts, interplant assignments foster the development of production know-why.⁴

A causal understanding of its production systems is key to any firm's continued ability to increase productivity (Teece & Pisano 1994; Lapré et al. 2000; Hatch & Dyer 2004). Previous studies have broadly identified three ways in which production know-why supports manufacturing innovation. First, it provides a causal model of the production system that allows employees to understand the implications of their improvement ideas and make informed changes (Perrow 1984; Garud 1997); as a result, employees are less likely to propose changes that improve performance in one part of the system but reduce performance in another. Second, know-why sets the stage for novel production solutions that go beyond a firm's current capabilities as it “opens up opportunities for discontinuous steps of improvement by reframing a problem in radically different ways” (Kim 1993, p. 40).⁵ Third, since abstract knowledge (such as know-why) is more universal than general knowledge (such as know-how), it offers a long-lasting basis for manufacturing innovation (Arora & Gambardella 1994). Building on these arguments, we hypothesise that interplant assignments increase employees' ability to generate valuable improvement ideas in the long term by stimulating conceptual learning and the development of production know-why.

HYPOTHESIS 3 (H3). After interplant assignments, employees' improvement ideas are permanently more valuable.

Underlying H3 is the reasoning that, through interplant assignments, individuals are exposed to stimuli from different but related contexts and learn from these stimuli by updating internal theories with new information. Yet if the contexts are too distant and lack common ground, then the information so conveyed is not related enough to help employees build a coherent theory. As summarised by Fiol and Lyles (1985), “the development of associations requires both change and stability” (p.806). At a basic level, stimuli must be generated by similar structural relationships in order for employees to identify the structures and then to formalise them into a theory (Reber 1989). Schilling et al. (2003) refer to this requirement as “related variation”: individuals cannot link learning from one context to another unless the two contexts are related.

⁴ Similar arguments about the acquisition of abstract knowledge have been made in the organisational learning literature (Fiol & Lyles 1985; Crossan et al. 1999).

⁵ See Marengo et al. (2000) for a formal analysis of reframing in organisational problem solving.

In this case, the stimuli are employees' observations of different instances of production know-how. Recall that the "relatedness" of two plants' production know-how depends on their functional overlap, or the similarity of their products, processes, and machinery. A crucial consequence is that, if there is insufficient functional overlap, then employees will be unable to distinguish important covariations—in other words, those that feed into theory building—from other variations, many of which are due to extraneous differences in the plant setups. The development of production know-why is limited under these circumstances. Hence we posit that the effect of interplant assignments on conceptual learning is stronger when employees are assigned to plants that have high functional overlap.

HYPOTHESIS 4 (H4). The long-term effect of interplant assignments on employee idea values is stronger if there is high functional overlap between the plants.

3 Analysis

3.1 Setting

The setting for our study is a large multinational car parts manufacturer based in Europe. This company supplies components to major car manufacturers worldwide as a "first-tier supplier". Between 2006 and 2012, the firm enjoyed average annual revenues of €3.9 billion across all its business units and of €1.6 billion from its core business unit—which produces the car components and is the focus of our study. The company supplies its customers from 14 plants in Europe, the Americas, and Asia.

The firm seeks to increase its production efficiency by way of a global employee innovation programme, on which our analyses are based. To develop a better understanding of this programme, its context, and interplant assignments, one of the authors conducted eight interviews with key managerial and operational employees from the company—interviews that informed the following description. The programme's goal is to increase the production efficiency of plants by systematically eliciting, evaluating, and implementing employee improvement ideas. Improvements are targeted at all products and all parts of the manufacturing process, including production, product costs, acquisition strategy, development, and overhead costs. Only manufacturing employees at the company's plants can participate; the programme is not open to R&D employees.

The centrepiece of the programme is a global database, into which employees enter their ideas and that is used to track idea evaluation and implementation. Submitting ideas is voluntary and is not part of employees' job requirements. To increase the number of idea submissions, the database interface is easy to use and the company encourages employees to submit all their ideas for potential improvements, regardless of perceived quality or other factors. All submitted ideas are independently evaluated by the accounting department according to a standardised process. Because the firm is looking to increase production efficiency, improvements are evaluated in terms of cost savings over a three-year period (to allow for the amortisation of potential upfront investments). If the evaluation indicates that implementing an idea would yield net positive cost savings, the improvement is adopted. For example,

in 2007 an employee at a European plant suggested a process optimisation that would reduce a machine's cycle time by 12.68%. The idea was evaluated to save the company €102,770 over three years and was thus implemented (see Figure 1).

--- Insert Figure 1 about here ---

The idea database is not connected to any human resources system and the company does not use idea submissions directly (e.g., in appraisals) to assess employee performance (e.g., for promotion) or to select employees for assignments. However, there may be indirect links between employees' idea submissions, informal recognition, and assignments. We address such concerns in the model specification and with additional robustness checks.

3.2 Data

The sample consists of all ideas submitted to the database between 2006 and 2010.⁶ From these data we create a balanced panel of employee-month observations,⁷ which allows us to use employee fixed effects. We exclude ideas from teams (since we cannot identify the team members) and ideas for which the data fields are not consistent.

--- Insert Table 1 about here ---

Table 1 summarises the data set by giving an overview of the main sample (column [a]) and the matched samples (columns [b]–[d]; the matching procedure is described in §3.7). The data comprise 21,131 ideas, of which 49% have been implemented. Over our four-year study period, 2,466 employees (28% of all factory staff) contributed an average of 8.57 ideas each.⁸ During the same time, 222 employees were assigned to a different plant. Some employees were assigned more than once, and there are 336 assignments in total. However, most employees were assigned only once, and no employee was given more than four such assignments. Ideas submitted to the database resulted, altogether, in cost savings of about €800 million between 2006 and 2012;⁹ this sum is equivalent to 8% of the business unit's revenue over the same period. The average idea value is €37,891 over three years.

3.3 Dependent Variable

To measure the value of implemented improvement ideas, we use the cost savings calculated by the accounting department. The calculation proceeds as follows. When submitting an idea, employees provide a description of the suggested improvement, an implementation plan, and an initial estimate of

⁶ A subset of 944 process improvement ideas together with additional data was used in Fuchs et al. (2019) to investigate how initial idea value estimates (which were available for that subset of 944 ideas) deviate from final (real) idea values. This is not an issue in the present paper, as we only use the final (real) idea values.

⁷ The average tenure at the company is 13 years for front-line workers and first-level supervisors (line heads, foremen, etc.); for all higher levels of management, the average tenure is 15 years.

⁸ The maximum number of ideas submitted over the four years by any one employee was 806. Excluding the three employees with significantly more ideas (304, 403, and 806) than all other employees did not materially affect our results.

⁹ Idea value is measured over the three years after an idea was submitted. Thus the value of an idea submitted in 2010 was measured until 2012.

costs and benefits. After the accounting department’s initial review of this information, the firm decides whether (or not) to proceed with the idea; if so, then the employee who submitted it is given standardised templates for providing further information about the improvement. Such information includes schematics describing the improvement in detail as well as operational data. Given this additional information, the accounting department checks whether the improvement is feasible and calculates the expected cost savings over the next three years.¹⁰ The department’s calculations consider, inter alia: data provided by the employee; additional data from supervisors, technical experts, and “process owners”; and, depending on the improvement, data on production volumes, the purchasing prices of input materials, energy consumption, energy prices, and labour costs. The resulting value is the net amount of cost savings (over three years) minus the implementation costs. If an idea’s net cost savings are positive, the idea is implemented.

Once an idea has been implemented, the cost savings for the current fiscal year are updated with actual performance data and the estimates for future years are adjusted accordingly. The accounting department reports only to corporate top management and is an independent unit tasked with carrying out a “fair evaluation of ideas”.¹¹ Its calculations are therefore a reliable comparative measure of the value of employees’ production improvements.

We calculate the dependent variable as follows. Let I_e (resp., I_{et}) denote the set of all ideas submitted by employee e (resp., in month $t \in T$). Then the average value \bar{v}_{et} of all ideas $i \in I_{et} \subseteq I_e$ submitted by employee e in month $t \in T$ is

$$\bar{v}_{et} = \frac{\sum_{i \in I_{et}} v_i}{|I_{et}|},$$

where v_i denotes the value of idea i as calculated by the accounting department; $\bar{v}_{et} = 0$ if $|I_{et}| = 0$.¹²

3.4 Explanatory Variables

We study interplant assignments across the company’s 14 plants in eight countries. The idea database is accessible from all plants, and ideas are linked to the plant from which they were submitted. To detect interplant assignments, we follow the prior literature and infer assignments from ideas submitted by the same employee e at different plants; this is a common approach to tracking employee mobility (Almeida & Kogut 1999; Song et al. 2003; Singh 2008; Singh & Agrawal 2011). In the Appendix, we use Monte Carlo simulations to examine this approach’s sensitivity to unobserved assignments.

¹⁰ Including the year of submission. We use year-month dummies to control for seasonality in submission.

¹¹ In the robustness checks (see the Appendix) we check for whether ideas from the country in which the accounting department is based are evaluated more favourably than ideas from other countries.

¹² We exclude adjusting entries (meant to balance aggregate idea value with accounting data) and ideas whose implementation spanned more than one year. All results continue to hold if we instead use total monthly idea value $v_{et} = \sum_{i \in I_{et}} v_i$ as the dependent variable.

Although we use ideas to track employee assignments, it is noteworthy that assignments are triggered by operational needs rather than by employees' idea generation or work performance. The company's central planning department assigns employees to different plants to address minor issues in production that require their expertise or manpower (cf. Bonet & Salvador 2017). Such problems are usually resolved within a few days, after which employees return to their home plants; few employee assignments last longer than two weeks. The following anecdote illustrates how employee assignments are triggered. In 2009, a plant was experiencing unstable metallisation throughput.¹³ The local staff were unable to resolve the issue, so an employee with expertise in metallisation was requested from another plant. The company employs several such employees, one of whom was selected by the planning department based on her availability. After a couple of days, she returned to her home plant. This example illustrates that an assignment is not due to employee submission of ideas or participation in the firm's improvement programme. Rather, exogenous problems trigger assignments and ideas are a by-product.

To capture the effects we have posited (in the referenced hypotheses), the following variables were used for employee e in month t .

Assignment (H1). This is a dummy variable that indicates whether an employee was assigned to a new plant during a given month; thus $Assignment_{et} = 1$ if employee e was assigned during month t , and $Assignment_{et} = 0$ otherwise. We use this variable to measure the short-term effect of assignments on idea value.

Post-assignment (H3). This indicator variable is set equal to 1 in all months after an employee has returned from an assignment to a new plant (we control for repeated assignments). We use this variable to measure the long-term effect of assignments on idea value:

$$Post\text{-}assignment_{et} = 1\{\exists k \in T : k < t, Assignment_{ek} = 1\}.$$

Last assignment (post hoc analysis). The discrete variable *Last assignment* increments by 1 for every three months since the last assignment. We use this variable in an additional post hoc analysis to measure how idea value develops over time after an employee has returned from an assignment:

$$Last\ assignment_{et} = Step_3(t - \max\{k \in T : k < t, Assignment_{ek} = 1\});$$

here $Step_3$ is a three-month step function,¹⁴ and $Last\ assignment_{et} = 0$ only if there is no $k < t$.

Assignment direction (H2, H4). We use assignments in which an employee was moved between different types of plants to measure the effect of functional overlap. The manufacturer we are studying distinguishes between two types of plants: central and peripheral. This distinction is equivalent to the distinction between lead factories and server factories, where the former are responsible for "new processes, products, and technologies for the entire company" while the latter "supplies specific

¹³ Metallisation is the process of applying a metal coating to other materials, for instance to glass in the production of mirrors.

¹⁴ Re-running our analyses with two-month and four-month step functions resulted in similar findings.

national or regional markets” (Ferdows 1997, p.76; Lang et al. 2014). The firm operates three central plants and eleven peripheral plants.

First, *Assignment direction_{et}* captures the short-term effect of assignments (H2) and represents one of four possible directions from a home plant¹⁵ to a receiving plant (the directions are named from the perspective of a central plant). These directions are central to central (“central” assignments), peripheral to central (“inbound” assignments), central to peripheral (“outbound” assignments), and peripheral to peripheral (“peripheral” assignments). The variable *Assignment direction_{et}* = 0 if (a) *Assignment_{et}* = 0 or (b) employees are assigned to more than one plant type in the same month (there are 25 cases of multiplant assignments).

Second, we construct direction-specific variables that capture the long-term effect of assignments (H4) in a way that is similar to how we constructed *Post-assignment_{et}*:

$$\begin{aligned} \textit{Previous assignment direction}_{et} &= \textit{Assignment direction}_{ek}, \\ k &= \max\{l \in T : l < t, \textit{Assignment direction}_{el} \neq 0\}; \end{aligned}$$

note that *Previous assignment direction_{et}* = 0 if there is no $k < t$. In our analyses, the variables are split into four dummy variables (one for each direction) and *(Previous) assignment direction_{et}* = 0 (no assignment) is the base value.

The firm’s distinction between central and peripheral plants and their differences in processes, machinery, and products allow us to operationalise functional overlap for different assignment directions. Table A1 summarises the differences between the plant types. In the focal firm, there is low functional overlap between central plants because each one is the lead manufacturer for a non-overlapping set of products (i.e., every product has exactly one manufacturing lead). Hence central plants differ in terms of the main product they produce. There is also low functional overlap between central plants and peripheral plants because central and peripheral plants differ in terms of their manufacturing processes and machinery. Central plants use and develop the newest manufacturing technology, whereas peripheral plants employ established technologies (cf. Lang et al. 2014). However, there is high functional overlap between peripheral plants, because all of them produce an overlapping range of products and use similar, established manufacturing technologies and processes. Thus, for the focal firm, there is high functional overlap between peripheral plants and low functional overlap between other types of plants.

3.5 Control Variables

To account for dynamic changes in employee ability, skills, idea submissions, and assignments, we include the control variables described next.

Repeated assignments. Some employees are assigned to different plants more than once. We control for this by counting the number of assignments after an employee’s first assignment.

¹⁵ The home plant is the one where employees have submitted the majority of their previous ideas.

Ideas submitted. We infer assignments from idea submission and to distinguish between the two, we must control for whether an employee has submitted any ideas.

Last idea submission. We control for the number of months since the last idea was submitted. Much as just described for *Ideas submitted*, we use this variable to distinguish between idea submission and assignments. This variable also allows us to control for employees' current involvement in the innovation programme. For example, employees may become caught up in their day-to-day work and lose touch with the current state of improvements.

Previous ideas submitted. We control for the number of ideas an employee has submitted before a given month. This variable allows us to control for employees' accumulated experience and knowledge over time.

Previous implementation rate. We control for the proportion of an employee's previous ideas that have been implemented (zero if no ideas have been implemented). Across all employees, on average 49% of ideas are implemented. Similarly to *Previous ideas submitted*, the *Previous implementation rate* variable allows us to control for changes in an employee's ability to generate good ideas.

Previous average idea value. We control for the average cost savings of an employee's previous ideas. Once again, we use this variable to control for an employee's changing ability to create economic value—as when an employee's increasing experience leads, over time, to ideas that are more valuable.

3.6 Fixed-effects Model

In the main models we use employee fixed effects to control for confounders that are constant over time; examples include employee ability, skills, and expertise. Although such unobservable factors could increase idea value as well as employees' likelihood of being assigned, we control for them completely with the employee fixed effects. Therefore, coefficients in the fixed-effects models are estimated using within-employee variation. These coefficients can generally be interpreted as the *additional* cost savings that an employee will generate because of an assignment. We also include time fixed effects (year-month dummies) to control for yearly and monthly seasonality (e.g., state of the firm, proximity to the fiscal year's end, holiday seasons).

In addition to employees' constant characteristics, we also consider how their ability, skills, and expertise change over time. As employees become more technically experienced, for example, they might be more likely to be sent on assignments and may also submit better ideas. Because such dynamic changes in confounders are not captured by employee fixed effects, we control for them by accounting explicitly for accumulated experience. There are two possible outcomes of accumulated experience with respect to idea value: employees will either submit better ideas or they will submit worse ideas; we address both cases with control variables that account for possible improvement (or deterioration) in idea quality over time. More specifically, we control for the number of *Previous ideas submitted*, the *Previous implementation rate* of submitted ideas, the *Previous average idea value*, and the number of *Repeated assignments*.

For employee e in month t , the fixed-effects regression takes the form

$$\bar{v}_{et} = \beta X_{et} + \gamma C_{et} + a_e + \delta a_t + u_{et}.$$

Here \bar{v}_{et} is the average value of all ideas submitted by employee e in month t , X_{et} is the vector of explanatory variables, C_{et} is the vector of control variables, a_e is employee fixed effects, and a_t represents year-month dummies.

3.7 Coarsened Exact Matching

Employees with more relevant expertise may be selected more often for assignments and may also have better ideas. To further address such concerns, we run all analyses in samples that match employees who are assigned (treated) with employees who are not assigned (controls) on a set of pre-assignment performance criteria. The aim of this procedure is for employees on assignments and control employees to be comparable, after matching, in terms of their pre-assignment ideas and environment. To achieve this, we match employees from the same home plant along four individual pre-assignment performance dimensions: number of ideas, implementation rate, average idea value, and time since their first idea. In other words, members of the treatment and control groups have worked at the same plant and have submitted similar numbers of implemented ideas, their ideas have generated similar cost savings, and they have been submitting ideas for about the same amount of time.

To perform the matching, we choose *coarsened exact matching* (CEM) over other matching algorithms, because it allows us to reduce the imbalance between treated and control groups on one variable without worsening the balance on another variable (Iacus et al. 2011). If one assumes that the previously described matching criteria do in fact identify control employees who are comparable (pre-assignment) to treated employees, then CEM reduces both model dependence and statistical bias. Coarsened exact matching has been repeatedly used for these purposes in economics and management research (e.g., Azoulay et al. 2010; Singh & Agrawal 2011).

Treated and controls are matched on a per-assignment basis, with each control matched to no more than one assignment. Employees who participate in more than one interplant assignment are matched to different controls for each assignment. If there is no matching control for one assignment, then that assignment is excluded from the matched sample. Suppose, for instance, that an employee is assigned twice but there is no match for the second assignment; in that case, we include the employee and the first assignment but exclude the second assignment. Hence we report more conservative estimates in the sense that any positive effect from the excluded second assignment reduces the reported short-term coefficients. We also exclude employees whose assignments could not be matched as well as all unmatched controls (the exact matching procedure is described in the Appendix).

All interplant assignment variables are calculated for control employees from the period that they were matched. This allows us to compute the average treatment effect or regression difference-in-differences (DD), while controlling for effects that may co-occur with an employee's assignment. For employee e in month t , the DD regression takes the form

$$\bar{v}_{et} = \beta_A X_{et} + \beta_M X_{et} \times M_e + \gamma C_{et} + a_e + \delta a_t + u_{et}.$$

In this expression, X_{et} is the vector of explanatory variables, M_e is a vector identifying treatment status (the constant M_e term is included in the employee fixed effects a_e), $X_{et} \times M_e$ is the interaction of explanatory variables with treatment status (the average treatment effect), and C_{et} is the vector of control variables; the terms a_e and a_t capture (respectively) employee fixed effects and year-month dummies.

4 Results

Table 2 presents descriptive statistics. Employees in the matched samples tend to have more and better ideas than those in the original sample, which suggests that our matching reduced the imbalance between treated and controls. Indeed, consistently lower \mathcal{L}_1 -statistics and smaller mean differences between treated and control groups demonstrate the improved balance in our matched samples (see Table 3). Nonetheless, implementation rates in the matched samples are almost identical to those in the full sample (around 49%). In the rest of this section we present the main results of our analyses. Additional robustness checks and our analysis of sensitivity to unobserved assignments are described in the Appendix.

--- Insert Tables 2 and 3 about here ---

4.1 Short- and Long-term Effects of Interplant Assignments (H1, H3)

We begin by discussing the results that are relevant to Hypotheses 1 and 3, which are reported in Table 4. Results based on the panel model with employee fixed effects (FE) are given in the first column, and those from the difference-in-differences model in the matched sample are in the second column (DD). Coefficients in the “treated” column of the matched sample are the average treatment effect for assigned employees (β_M). The way to interpret the coefficients is in terms of changes to the average cost savings that all ideas submitted during a given month will generate over the next three years (see §3.3 for a description of how cost savings are calculated by the accounting department). All standard errors are clustered at the employee level and are robust to heteroskedasticity and autocorrelation (Wooldridge 2010).

--- Insert Table 4 about here ---

Hypothesis 1 predicts that assignments to different plants will increase the value of employees’ process and product improvement ideas in the short term by stimulating knowledge transfer. The coefficients for the dummy variable *Assignment*, which indicates whether (or not) an employee was assigned to a new plant during a given month, are positive and significant in the FE and DD models. An assignment increases the value of ideas submitted in the same month by €151,340 in the FE model and by €133,550 in the DD model (over three years). As expected, control employees who are similar to the treated employees yet stay at their home plant do not benefit from their colleague’s assignment. The coefficient in the DD model is slightly smaller than—but of the same order of magnitude as—the FE coefficient. The R^2 of 3%–4% is low, but this is not uncommon in studies on employee mobility and

knowledge transfer (e.g., Argote et al. 2018) and often reflects highly disaggregated individual-level data (Singh & Agrawal 2011).

Hypothesis 3 predicts that employee assignments to different plants will increase the value of their process and product improvement ideas in the long term by stimulating conceptual learning and creating production know-why. The coefficients for the indicator variable *Post-assignment*, which is set to 1 in all months after an assignment (while controlling for repeated assignments), are positive and significant in the FE and DD models. After employees have returned from an assignment, their average idea value increases by €23,720 (resp. €26,050) in the FE (resp. DD) model.

4.2 Time-varying Effects of Interplant Assignments

To investigate the time-varying effects of interplant assignments, we relax the restriction that the post-assignment effect be constant by introducing several dummy variables that partition the post-assignment period into three-month intervals (*Last assignment*). Assignments are distributed evenly during our sample period and there is a sufficient number of assignments at the beginning (see Figure A1 in the Appendix). Figure 2 graphs the main fixed-effects model and Table 5 reports the estimates of our analyses.

--- Insert Table 5 & Figure 2 about here ---

With respect to Hypothesis 1 (Operational Learning), we can see in both the FE and DD models that idea values in the first three months after an employee's return are not significantly different from their pre-assignment levels. In other words, after an assignment, employees' innovation performance initially reverts back to what it was before the assignment. This is consistent with previous observations that the limits of operational learning are reached quickly once all "low-hanging fruits" of improvements have been reaped (Mukherjee et al. 1998).

With respect to Hypothesis 3 (Conceptual Learning), we observe that after six (FE model) to nine (DD model) months, employees begin to submit significantly better ideas again, and that this increase in the value of ideas persists until the end of our study period (up to 48 months). The three-month interval effects are of the same order of magnitude (viz., between €17,930 and €43,280) as the constant effect estimated in the previous long-term models. These additional results indicate two aspects of how learning evolves over time. First, conceptual learning does not seem to occur immediately. Rather, production know-why appears to develop gradually as employees incorporate observations from the destination plant into their conceptual frameworks and iteratively align those observations with their home-plant experiences. Second, consistent with prior work, once such know-why is acquired, it remains relevant for a longer period of time (Kim 1993; Arora & Gambardella 1994; Garud 1997; Mukherjee et al. 1998).

4.3 Functional Overlap between Plants (H2, H4)

Table 6 summarises the results relevant to functional overlap (H2 and H4). The main model is the fixed-effects model in the full sample (FE). We also report the results of three difference-in-differences

models (DD1, DD2, and DD3) in two separately matched samples of peripheral and central employees. As before, the coefficients in the “treated” columns of matched samples are the average treatment effect for employees on interplant assignments (β_M). Coefficients should be interpreted as changes in the average three-year cost savings of all ideas submitted during a given month. All standard errors are clustered at the employee level and are robust to heteroskedasticity and autocorrelation (Wooldridge 2010).

--- Insert Table 6 about here ---

Hypothesis 2 and 4 predict that assignments to plants with high functional overlap will increase knowledge transfer (H2) and employee learning (H4) more than will assignments to functionally dissimilar plants. We use assignments between different plant types to measure the effect of functional overlap. Our prediction was that, of the four possible assignment directions described in §3.4, it is only with peripheral-to-peripheral assignments—where products, processes, and machinery are similar—that there is sufficient functional overlap for knowledge transfer and employee learning to occur. Supporting the functional overlap hypotheses, the coefficients of both *Peripheral assignment* dummy variables are significant in the short term (*Peripheral assignment*, H2) and strongly significant in the long term (*Previous peripheral assignment*, H4) in the main FE model. Assignments to functionally similar plants increase idea value by €229,230 in the same month and by €40,490 in the long term. The short-term estimates for H2 are large and positive; however, they are statistically weaker than both the short-term estimates for H1 and the long-term estimates for H4. These results suggest that knowledge transfer depends less consistently on functional overlap than learning. At the same time, there is no evidence that knowledge transfer is stronger in any other assignment direction: the estimated coefficients for central and outbound assignments are small and not significant; and the significant estimate for inbound assignments disappears in the matched sample of peripheral employees (DD1), which suggests that it was driven by differences between peripheral and central employees.

A possible alternative explanation for these results is that the employees at each type of plant are different. For example, employees at central plants may be too busy or too skilled to benefit from assignments. To rule out such alternative explanations, we conduct further analyses and provide additional evidence in support of the functional overlap hypotheses using DD models and *t*-tests.

First, we study assignments from peripheral plants separately to compare the effects of peripheral assignments (peripheral to peripheral, with high functional overlap) and inbound assignments (peripheral to central, low functional overlap) only for employees at peripheral plants. This allows us to remove any part of the effect that could be due to peripheral employees benefitting more from assignments than central employees. As shown in column DD1 of Table 6, the results in the matched subsample of peripheral employees are very similar to the results in the full sample (a €237,220 short-term effect and a €36,440 long-term effect). Thus, the results in the full sample are not driven by peripheral employees systematically benefitting more from assignments.

Second, we assess whether employees at central plants are busier or better at generating ideas than peripheral employees. We make two observations: (i) there is no significant difference between central and peripheral employees in terms of the number of ideas submitted (8.78 vs 8.72, $p = 0.96$);¹⁶ and (ii) neither is there a significant difference in the total cost savings generated (€347,090 for central employees vs €315,470 for peripheral employees, $p = 0.72$). Thus we can rule out that employees at central plants are too busy to submit ideas or that their ideas are inherently better. If that were the case, we would expect significant differences in terms of idea submission and idea value between central and peripheral employees.

Third, we analyse assignments from central plants separately. There is low functional overlap between central plants (different products) and between central plants and peripheral plants (different manufacturing processes). It is therefore unsurprising that we find no significant positive effect in the matched sample of central employees (DD2). This finding supports our hypotheses, but it would be preferable to compare assignments between plants with a somewhat higher functional overlap to those with lower functional overlap for central employees as we did for peripheral employees in DD1.

For that purpose, we use high-level information on product categories at different plants. The company produces two types of car parts (A and B) that belong to the same product family but are used in different places on cars and have different functional requirements. Following our theoretical discussion, we would expect that assignments from central plants to peripheral plants that produce products in the same category (A to A) overlap more than assignments to peripheral plants that produce products in the other category (A to/from B).¹⁷ The regression results are presented in column DD3 of Table 6. The long-term effect (H4) of assignments to peripheral plants in the same product category is positive, significant, and of the same order of magnitude as our earlier estimates (€33,370); in contrast, the baseline effect of an assignment to a peripheral plant that makes different products is small and not significant. The equivalent short-term effect (H2) is large and positive but not significant, which is in line with our weaker estimate for the short-term effect in the FE model. Thus, together with the main FE model, the additional DD models offer consistent evidence in support of the functional overlap effect, which appears to be stronger for employee learning (long-term effect) than for knowledge transfer (short-term effect).

4.4 Limits to Interplant Assignments

We now engage in a series of post hoc analyses to explore potential practical limits of interplant assignments. We begin with plant-level constraints on the number of outbound assignments over a given time period. The average annual assignment rate in our sample is 3.41% of the workforce, which is within the company's estimated range of between 3% and 5%. As more employees are assigned to other

¹⁶ The average number of ideas is higher in the matched samples because the matching reduces some of the imbalances.

¹⁷ We do not compare assignments between central plants, because each central plant is the lead manufacturer for a non-overlapping set of products.

plants, we expect that their respective home plants' production will become increasingly disrupted. Although we have no data on production volumes or labour costs, we demonstrate in additional analyses that the likelihood of additional outbound assignments declines as the cumulative assignment rate at a plant increases.¹⁸ Thus there appear to be increasing disutilities from outbound assignment, which need to be taken into account when designing assignment programmes. In our sample, plants tend not to exceed an assignment rate of around 3%.

In a second step, we assess whether there are decreasing returns from interplant assignments with respect to knowledge transfer (H1) or employee learning (H3). In terms of knowledge transfer, we find no decreasing returns as either the cumulative rate or the absolute number of outbound assignments at a plant increases. Therefore, employees do not transfer less knowledge as more of their colleagues are being assigned to other plants. Yet we do find decreasing returns if we count assignments between plant dyads: as the number of assignments from one plant to another increases, knowledge transfer between those two plants decreases. Figure 3 plots these results.

--- Insert Figure 3 about here ---

The base model is the fixed-effects model for H1 (Table 4, FE) but without the *Post-assignment* variable. We then estimate three separate models that interact the *Assignment* variable with the cumulative number of dyadic outbound assignments over the last 3, 12, and 48 months. The interaction effect is significant at 3 months (−35,230 euros per additional outbound assignment, $p = 0.077$; solid line in the graph) but not at 12 months (−17,700 euros, $p = 0.161$; dashed line) or at 48 months (−2,200 euros, $p = 0.747$; dotted line)—which suggests that only recent dyadic interplant assignments reduce knowledge transfer. After more than five outbound assignments in each direction over three months, we estimate no significant additional knowledge transfer. In terms of employee learning (H3), there are no decreasing returns from either plant-level or dyad-level cumulative outbound assignments in similarly specified models, which is what we would expect given the individual learning mechanisms described in §2. We also examine how employees' previous assignments and idea submissions influence knowledge transfer and employee learning, but we find only two small effects: *Previous average idea value* slightly increases idea values during assignments (0.83, $p < 0.05$); and more time since the *Last idea submission* slightly decreases idea values (−6.27, $p < 0.05$).

5 Discussion

Do interplant assignments affect employee-driven manufacturing innovation? Using various econometric models, we show that such assignments increase front-line innovation by facilitating

¹⁸ We use a linear probability model with plant fixed effects (and robust standard errors clustered at the employee level) as well as a conditional fixed-effects logit model with bootstrap errors (1,000 repetitions). Controlling for fewer assignment opportunities, both models exhibit a decline in the likelihood of additional assignments as the number of cumulative assignments over the last twelve months increases. The ordinary least-squares estimate (−1.16) is significant at $p = 0.03$; the logit estimate (−9.91) is not significant ($p = 0.128$), but exhibits a similar slope.

knowledge transfer and stimulating employee learning. Whereas knowledge transfer increases innovation during and shortly after assignments, employee learning increases innovation in the long run. The functional overlap between assignment plants (i.e., the similarity of products, processes, and machinery) influences both employee learning and (to a lesser degree) knowledge transfer. Previous research has argued that sustained manufacturing innovation depends on a mix of operational and conceptual learning (Kim 1993; Mukherjee et al. 1998), and our findings establish that interplant assignments play an important role in both learning processes.

Given these results, how should firms implement interplant assignments? Although the design of an optimal assignment policy is beyond the scope of this study, we identify a range of practical boundaries within which assignments make sense. As expected, there appear to be increasing disutilities as a plant's assignment rate—the proportion of its workforce participating in assignments—rises (for instance, because of understaffing). As a result, plants in our sample tend to stay below annual assignment rates of 3%. In addition, knowledge transfer between two plants decreases as more employees are exchanged between them. We find that knowledge transfer abates after about five assignments in each direction over a period of three months. Therefore, assignments should be spread out equally over time and between different destinations in order to maximise knowledge transfer and avoid production disruptions. In contrast to knowledge transfer, individual conceptual learning is not affected by cumulative assignments between plants.

5.1 Contributions to Theory

This study provides insight into manufacturing innovation and learning across organisational units. First, we extend the literature on employee mobility to individual innovation outcomes. While previous studies have found job performance to be reduced after moves between firms (Groysberg et al. 2008; Dokko et al. 2009; Raffiee & Byun 2020) and when work is distributed within firms (MacDuffie 2007; Bonet & Salvador 2017), we show that despite such potential negative effects on productivity, within-firm mobility increases individuals' contributions to innovation. We do not possess data on job performance, so we cannot say definitively whether one outweighs the other, but we estimate economically significant short and long-term cost savings from boosted employee innovation. We elaborate in the next section how this trade-off between employee productivity and innovation provides promising opportunities for future empirical and analytical research.

Second, previous research has cast doubt on the extent to which employees can transfer know-how between organisational contexts (e.g., Szulanski 1996; Huckman & Pisano 2006; KC & Staats 2012). In particular knowledge related to technical problem solving is often “sticky” and difficult to transfer from the site at which it was acquired (von Hippel 1994). In addition, empirical studies in manufacturing have argued that production know-how is “by and large not retained by the plant's workers” (Levitt et al. 2013, p.679) but rather becomes “embedded in the organization's structure or technology” (Epple et al. 1996, p.84). In contrast, we find evidence to suggest that production know-how is transferred

between plants by individual manufacturing workers. To reconcile our findings with the existing literature, we make three observations:

- (1) Huckman and Pisano (2006) note that know-how may be asset-specific. In line with this argument, we find that employees transfer knowledge more easily between plants that have similar products, processes, and machinery. Thus, our findings suggest that production know-how is less sticky (i.e., easier to transfer) between plants with comparable assets (cf. von Hippel 1994; Tyre & von Hippel 1997).
- (2) As we argue in Hypothesis 1, involving workers in problem solving may be crucial for their access to and retention of production knowledge (cf. Hatch & Dyer 2004 for a related argument on worker involvement). Levitt et al. (2013) allude to this when stating that their results are “consistent with the plant’s systems for productivity measurement and improvement” (p.643), which rely almost exclusively on engineers to implement improvements and rarely involve workers.
- (3) Some of the literature’s conclusions on workers’ embodiment and transfer of knowledge were drawn in part from progress on aggregated learning curves (Epple et al. 1996; Levitt et al. 2013). Our findings based on granular worker-level data suggest that in these studies the presence of knowledge retention in organisational capital (such as machines and routines) may have masked the extent to which knowledge had also become embedded in workers. We therefore join Raffiee and Byun (2020) in cautioning against “generalising findings across levels” of aggregation when studying learning in individuals and organisations (p.38).¹⁹

Third, we contribute to the literature on individual learning (e.g., Boh et al. 2007; Narayanan et al. 2009) the notion that workers can acquire conceptual knowledge (know-why), which—instead of directly raising employees’ productivity—increases their ability to identify and implement opportunities for production improvement (cf. Hatch & Dyer 2004). We show that, similar to productivity learning from different *tasks* (e.g., Schilling et al. 2003; Staats & Gino 2012), conceptual learning occurs when employees are exposed to different *plants*, and that it is greater after assignments to related rather than unrelated plants. Unlike production know-how, which has frequently been estimated to depreciate quickly (Argote et al. 1990; Epple et al. 1996; Levitt et al. 2013), conceptual knowledge appears to boost employee innovation for several years. This resonates with prior arguments that conceptual or abstract knowledge becomes obsolete at a slower rate than general knowledge and know-how (Kim 1993; Arora & Gambardella 1994; Garud 1997; Mukherjee et al. 1998).

5.2 Limitations and Future Research

One limitation of this study is that we do not possess operational data or information about the production issues that trigger interplant assignments. This offers several opportunities for future

¹⁹ This also applies to the present study. As we mention in several places, our lack of data on productivity and the costs of assignments limits our ability to draw conclusions at the firm level.

research. For instance, detailed data on employees (e.g., their production method specialisation, individual productivity, and other HR-related information) may yield further insights into the effect of assignments on innovation. Given that the assignments in our sample are triggered by operational needs, it would also be interesting to investigate whether different types of assignments have different implications for innovation. Should firms send out employees to observe or to fix problems? In the former case, would employees still have sufficient access and exposure to destination plants' knowledge repositories? And how should employees be selected if assignments are *not* driven by operational needs? Given that we do not possess data on production volumes, labour costs, or travel expenses, we can only outline best practices for assignment management. This presents a promising opportunity for both analytical and empirical researchers to use our estimates as starting points for the design of an optimal assignment policy. Scholars could investigate, for instance, the trade-offs between production disruptions, short-term knowledge transfer, and long-term employee learning. Lastly, we operationalise functional overlap based on different plant types and the firm's configuration of these plants' products, processes, and machinery. While this operationalisation allowed us to shed new light on the role of peripheral plants in manufacturing innovation, we would like to encourage the further validation of this concept with more fine-grained measurements of plant differences. We believe that this can yield important insights into the roles of specific plants in the acquisition and transfer of production knowledge.

Interplant assignments—and employee mobility more generally—are widespread in many business settings. However, previous research in operations management has paid only limited attention to the phenomenon. This oversight is surprising when one considers that business operations often rely on some form of employee mobility. For instance, modern R&D organisations frequently work on globally distributed projects (see e.g. Gokpinar et al. 2013; Mishra & Sinha 2016), where site visits from developers play a pivotal role in complementing digital collaboration (Hinds & Cramton 2014). Employee mobility is also required by supply chain practices that span firm boundaries, such as supplier involvement and development (Clark 1989; Krause et al. 2007; Agrawal et al. 2014), vendor-managed inventory (Çetinkaya & Lee 2000; Lee & Whang 2000), and quality audits or inspections of suppliers (Babich & Tang 2012; Chen & Lee 2017). MacDuffie and Helper (1997) offer a vivid example:

Some Japanese companies have taken the unusual step of working extensively with their suppliers to teach them “lean production”—often by sending their own employees into supplier plants for weeks or months to redesign work stations, reorganize process flow, modify equipment, and establish problem-solving groups. This level of involvement with the internal operations of externally owned firms is unprecedented. (p.118)

By underscoring how interplant assignments can spark valuable ideas, we hope that our paper encourages operations management researchers to shed more light on the effects of employee mobility within and across firms.

We conclude by noting that our data comes from a single company, which calls for caution in generalising our results. Given the scarcity of micro-level data relating to multiple firms, studies of single firms are common in organisational learning (e.g., Tyre & von Hippel 1997; Staats & Gino 2012; Levitt et al. 2013). To aid generalisability, we provide rich contextual information on the focal firm, its implementation of interplant assignments, and its employee innovation programme. With similar innovation programmes now being used in many companies and the increasing emphasis on employee mobility, we want to encourage future work to verify and extend our findings by examining employee mobility and manufacturing innovation in a variety of other settings.

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Tables

Table 1: Overview of Samples

	[a] Full sample	[b] Matched sample	[c] Matched sample of peripheral employees	[d] Matched sample of central employees
Observations	118,368	21,648	12,480	8,736
Employees	2,466	451	260	182
Employees on assignments (treated)	222	198	114	84
Matched employees (controls)		253	146	98
Ideas	21,131	7,414	4,249	1,943
Implemented ideas	49%	49%	58%	48%
Assignments	336	253	146	98
Central assignments	20			14
Inbound assignments	69		60	
Outbound assignments	105			84
Peripheral assignments	117		86	

Note. No direction was ascribed to the 25 assignments that were to more than one plant type in the same month.

Table 2: Descriptive Statistics

Variable	[a] Full sample				[b] Matched sample				[c] Matched sample of peripheral employees				[d] Matched sample of central employees			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Average idea value	2.72	82.89	-7674	9120	8.07	130.53	-2335	8850	9.97	152.17	-3371	8850	5.07	104.89	-1570	6202
Assignment	0.00	0.05	0	1	0.01	0.11	0	1	0.01	0.11	0	1	0.01	0.11	0	1
Post-assignment	0.05	0.21	0	1	0.23	0.42	0	1	0.21	0.41	0	1	0.25	0.43	0	1
Last assignment	0.70	3.93	0	46	3.54	8.48	0	46								
Repeated assignments	0.02	0.18	0	4	0.04	0.26	0	4	0.04	0.24	0	3	0.03	0.18	0	2
Ideas submitted	0.06	0.25	0	1	0.11	0.31	0	1	0.12	0.33	0	1	0.09	0.29	0	1
Last idea submission	8.27	11.22	0	59	9.68	11.06	0	48	8.43	10.22	0	47	10.99	11.75	0	51
Previous ideas submitted	5.29	21.50	0	806	10.69	41.15	0	806	9.93	17.02	0	168	7.03	10.77	0	87
Previous implementation rate	0.24	0.37	0	1	0.35	0.38	0	1	0.36	0.37	0	1	0.30	0.36	0	1
Previous average idea value	26.98	204.98	-2937	9120	56.37	200.21	-2198	2513	74.49	228.20	-1886	2513	43.33	193.74	-2198	1257

Notes. Descriptive statistics are given per employee-month, and assignment variables are reported for the treated employees in the matched samples. The assignment direction variables are a subset of the assignment and post-assignment variables (see Table 1 for a breakdown).

Table 3: Balance Improvements in the Matched Samples

	[a] Full sample		[b] Matched sample		[c] Matched sample of peripheral employees		[d] Matched sample of central employees	
	\mathcal{L}_1 -statistic	Mean difference	\mathcal{L}_1 -statistic	Mean difference	\mathcal{L}_1 -statistic	Mean difference	\mathcal{L}_1 -statistic	Mean difference
Previous ideas submitted	0.42	5.84	0.10	-1.33	0.18	1.18	0.29	-0.40
Previous implementation rate	0.36	0.24	0.21	0.12	0.22	0.14	0.21	0.12
Previous average idea value	0.33	52.45	0.15	43.39	0.19	41.61	0.15	39.20
Time since first idea	0.41	3.54	0.29	-1.72	0.31	-0.20	0.23	-3.38

Note. A lower \mathcal{L}_1 -statistic and a reduced difference between the means of the treated and control groups indicates an improved balance in the matched samples (Iacus et al. 2011).

Table 4: Effect of Assignments on Average Idea Value

	FE	DD	
	Full sample	Matched employees (controls)	Assigned employees (treated)
Assignment	151.34*** (56.30)	-1.94 (2.06)	133.55** (62.07)
Post-assignment	23.72*** (6.97)	-0.56 (3.33)	26.05*** (8.05)
Repeated assignments	16.96* (8.66)		6.86 (18.35)
Ideas submitted	33.92*** (3.85)		58.13*** (6.63)
Last idea submission	0.03 (0.05)		0.04 (0.15)
Previous ideas submitted	-0.03 (0.06)		-0.01 (0.05)
Previous implementation rate	-0.34 (1.66)		-9.26 (5.89)
Previous average idea value	-0.07*** (0.01)		-0.04 (0.04)
Employee fixed effects	Yes		Yes
Year-month dummies	Yes		Yes
Intercept	0.09 (2.12)		-8.29 (7.70)
<i>F</i> -statistic	10.13		5.37
<i>R</i> ²	0.03		0.04
Observations	118,368		21,648
Employees	2,466		451

Notes. The dependent variable is expected cost savings in thousands of euros. Reported values are those derived from the main fixed-effects model (FE) and from the difference-in-differences model in the matched sample (DD). Robust standard errors (in parentheses) are clustered at the employee level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Time Since Last assignment on Average Idea Value

	FE		DD	
	Full sample	Matched sample		
		Matched employees (controls)	Assigned employees (treated)	
Assignment	151.01*** (56.06)	-3.33 (3.38)	133.97** (61.46)	
Last assignment (3 months)	4.98 (3.89)	-4.42 (4.50)	8.00 (5.77)	
Last assignment (6 months)	29.13** (14.40)	5.86 (8.66)	26.48 (17.12)	
Last assignment (9 months)	37.26*** (11.51)	-3.27 (4.21)	43.28*** (13.72)	
Last assignment (12 months)	27.64** (13.89)	-1.32 (5.39)	32.98** (15.75)	
Last assignment (15 months)	24.27** (11.29)	-2.80 (5.46)	18.83*** (7.10)	
Last assignment (18 months)	19.04*** (5.87)	-3.45 (6.31)	23.37*** (7.47)	
Last assignment (21 months)	22.63*** (7.02)	-0.83 (7.13)	23.84*** (8.57)	
Last assignment (24 months)	17.93*** (6.61)	-7.18 (7.34)	26.96*** (8.76)	
Last assignment (27 months)	20.51** (8.50)	-9.56 (8.31)	24.43** (10.30)	
Last assignment (30 months)	24.02*** (7.21)	-8.06 (8.98)	29.99*** (9.13)	
Last assignment (33 months)	27.10*** (10.27)	-10.99 (9.63)	37.48*** (11.67)	
Last assignment (36 months)	22.85*** (7.70)	-8.20 (10.38)	32.00*** (9.87)	
Last assignment (39 months)	30.91*** (8.96)	-4.33 (12.88)	33.70*** (12.19)	
Last assignment (42 months)	23.53*** (7.92)	-8.61 (12.82)	34.30*** (11.19)	
Last assignment (45 months)	24.99*** (9.41)	-1.52 (13.16)	32.89*** (11.71)	
Last assignment (48 months)	22.66** (9.02)	4.60 (13.75)	28.92** (11.84)	
Repeated assignments	16.63* (8.60)		6.16 (18.72)	
Ideas submitted	33.98*** (3.85)		58.19*** (6.55)	
Last idea submission	0.03 (0.05)		0.08 (0.17)	
Previous ideas submitted	-0.04 (0.06)		0.00 (0.05)	
Previous implementation rate	-0.31 (1.67)		-10.25* (5.75)	
Previous average idea value	-0.07*** (0.01)		-0.04 (0.04)	
Employee fixed effects	Yes		Yes	
Year-month dummies	Yes		Yes	
Intercept	0.08 (2.12)		-8.28 (7.70)	
<i>F</i> -statistic	8.41		4.93	
<i>R</i> ²	0.03		0.04	
Observations	118,368		21,648	
Employees	2,466		451	

Notes. The dependent variable is expected cost savings in thousands of euros. Reported values are those derived from the main fixed-effects model (FE) and from the difference-in-differences model in the matched sample (DD). Robust standard errors (in parentheses) are clustered at the employee level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of Assignment Direction on Average Idea Value

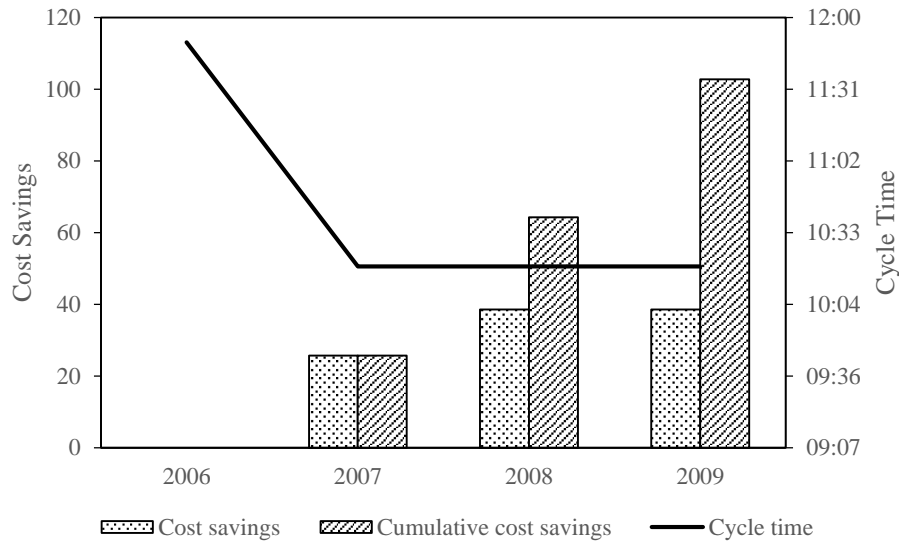
	FE	DD1		DD2		DD3	
	Full sample	Matched sample of peripheral employees		Matched sample of central employees			
		Matched employees (controls)	Assigned employees (treated)	Matched employees (controls)	Assigned employees (treated)	Matched employees (controls)	Assigned employees (treated)
Central assignment	-9.97 (18.41)			-6.99 (9.93)	-41.97 (42.08)		
Inbound assignment	166.19* (90.35)	1.58 (3.80)	55.27 (53.66)				
Outbound assignment to plant with similar products	6.99 (22.50)			-6.11 (4.18)	-17.56 (24.44)	-5.29 (4.85) -7.71 (5.63)	-34.23 (21.68) 82.53 (99.85)
Peripheral assignment	229.23* (122.55)	-0.61 (3.96)	237.22* (135.41)				
Previous central assignment	4.15 (6.90)			4.64 (5.39)	-11.86* (7.01)		
Previous inbound assignment	23.50 (15.30)	6.10 (5.06)	12.52 (11.68)				
Previous outbound assignment to plant with similar products	3.00 (5.83)			-0.27 (6.91)	8.29 (9.72)	0.82 (7.99) -3.65 (3.24)	4.15 (10.53) 33.37** (15.29)
Previous peripheral assignment	40.49*** (14.33)	2.52 (3.88)	36.44** (15.15)				
Repeated assignments	14.94* (8.38)		21.64 (28.82)		2.65 (6.34)		3.02 (6.83)
Ideas submitted	35.38*** (3.93)		63.73*** (8.17)		55.30*** (11.93)		54.24*** (11.82)
Last idea submission	0.03 (0.05)		0.05 (0.18)		-0.36 (0.30)		-0.34 (0.30)
Previous ideas submitted	-0.05 (0.06)		0.23 (0.25)		-1.63 (1.04)		-1.65 (1.04)
Previous implementation rate	0.03 (1.58)		-17.04** (8.01)		5.26 (7.67)		4.59 (7.47)
Previous average idea value	-0.07*** (0.01)		-0.03 (0.04)		-0.09*** (0.03)		-0.09*** (0.03)
Employee fixed effects	Yes		Yes		Yes		Yes
Year-month dummies	Yes		Yes		Yes		Yes
Intercept	-0.12 (2.12)		-6.74 (12.98)		-9.14 (6.96)		-8.77 (6.95)
<i>F</i> -statistic	9.35		4.69		17.79		18.96
<i>R</i> ²	0.03		0.05		0.04		0.04
Observations	118,368		12,480		8,736		8,736
Employees	2,466		260		182		182

Notes. The dependent variable is expected cost savings in thousands of euros. Reported values are those derived from the main fixed-effects model (FE) and from the difference-in-differences models in different matched samples (DD1–DD3). Robust standard errors (in parentheses) are clustered at the employee level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

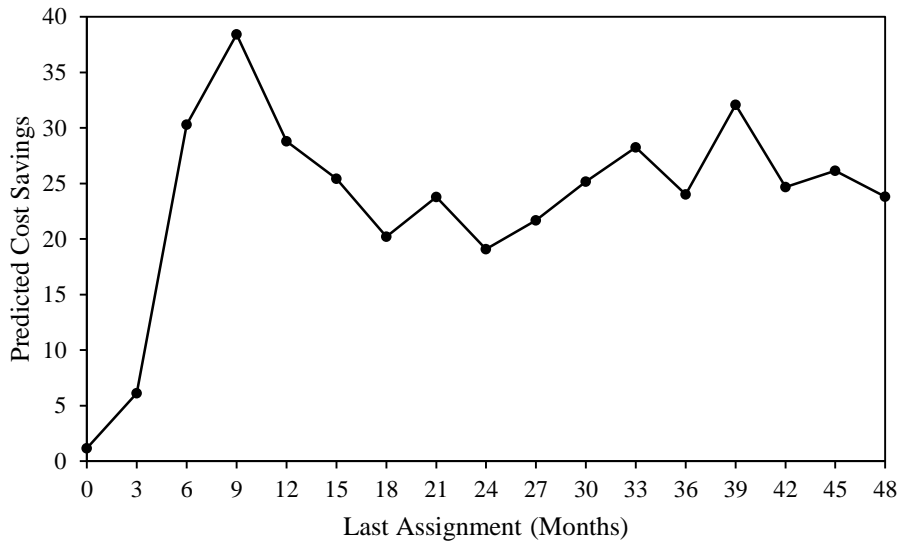
Figures

Figure 1: Cost Savings (over three years) Due to a Typical Process Optimisation Idea



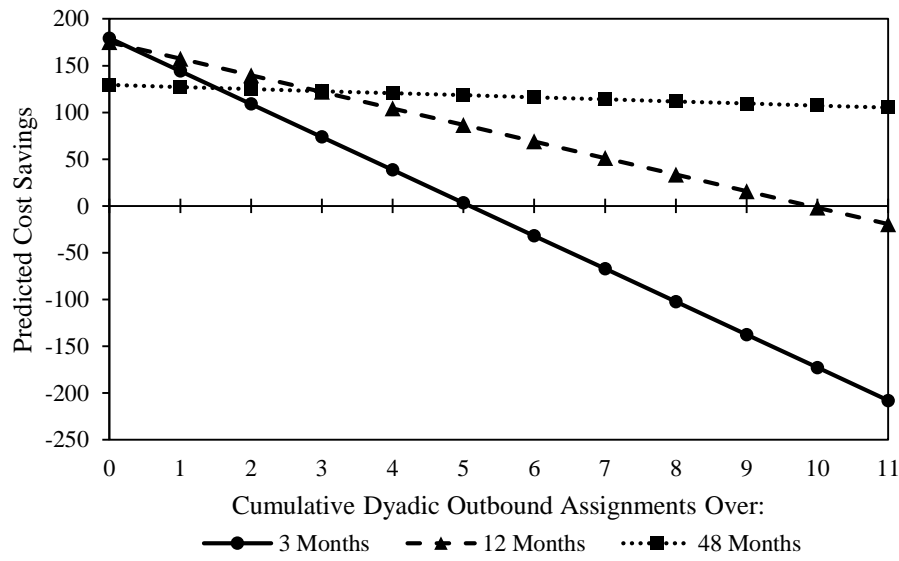
Notes. Cost savings are given in thousands of euros. This improvement idea led to a 12.68% reduction in cycle time (from 11:50 to 10:20). The idea was implemented in 2007 and led to cumulative cost savings of €102,770 (over three years).

Figure 2: Predicted Cost Savings after the Last Assignment (nonlinear FE estimates at three-month intervals)



Notes. Predicted cost savings are given in thousands of euros and are significant after six months (see Table 5). Here $Assignment_{et} = 0$ and all other variables are at their means.

Figure 3: Predicted Cost Savings during and Immediately after an Assignment (based on previous cumulative dyadic outbound assignments over 3, 12, and 48 months)



Notes. Dyadic outbound assignment from one plant to another. Plotted values are based on the fixed-effects model of H1 (FE column in Table 4) without *Post-assignment*. The slope is significant at 3 months (-35,230 euros, $p = 0.077$) but not at 12 months (-17,700 euros, $p = 0.161$) or 48 months (-2,200 euros, $p = 0.747$).