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Does Quality Knowledge Spillover at Shared Suppliers? An Empirical Investigation

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We use a unique empirical setting to investigate the spillover of quality knowledge across supply chains and to the examine contingencies that affect such spillover. We analyze the quality performance of 191 suppliers, who utilize the same facilities to manufacture similar products for two distinct businesses: one that makes cars and the other that makes commercial vehicles. From 2006 to 2009, the car business undertook 2,121 quality improvement initiatives at these suppliers, while the commercial vehicles business did not undertake any such initiatives. We find that the quality knowledge developed through the quality improvement initiatives undertaken by the car business does not easily spill over to benefit the commercial vehicles business. Quality knowledge spills over under three conditions: (1) when quality improvement efforts are focused on organizational members, as opposed to when they focus on routines or technology; (2) when quality improvement efforts focus on the output activities of suppliers, not when they focus on the input or in-process activities; and (3) when quality knowledge is developed at suppliers with low complexity in their operations. Our results provide insights on managing quality at shared suppliers.

Keywords: quality knowledge; shared suppliers; organizational learning; knowledge spillover
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1. Introduction

With the increased emphasis on outsourcing, many firms rely on their suppliers for a substantial amount of their manufacturing requirements. The quality performance of such firms often depends on the quality levels achieved by their suppliers. Consequently, given the link between quality and operating performance (e.g., Hendricks and Singhal 1997), many manufacturing firms naturally work with their suppliers to develop knowledge to address quality issues (we refer to this knowledge as *quality knowledge*) within their supply chains. Typically, such efforts are in the form of quality improvement initiatives that aim to address specific quality issues. The logic of working with exclusive (i.e., not shared) suppliers is straight forward, as the firm directly benefits from the suppliers' improved quality performance. However, often suppliers are not exclusive. They may also cater to the needs of other buyers, some of whom may be competitors. In such instances, improving quality at shared suppliers may have competitive implications (e.g., Banker et al. 1998) because it could also improve quality for other buyers. This is because when suppliers develop quality knowledge it is only natural for them to also use the knowledge to address other quality issues they may face in their facilities. Moreover, even when suppliers are disinclined to share this knowledge, other buyers may obtain the knowledge through their regular interactions with the shared suppliers or by observing the changes at the suppliers' facilities. In fact, Arrow (1963) points out that once knowledge is developed it is difficult to prevent it from being used or to prevent others from obtaining it. Therefore, it is likely that quality knowledge can spill over and lead to potential conflicts. On the one hand, if the spillover of quality knowledge is high, a firm may hesitate to improve the quality performance of a shared supplier because it may also benefit other buyers. On the other hand, if the spillover of quality knowledge is low, a firm would need to work with its shared suppliers because it will not benefit from quality improvement efforts undertaken by other buyers. Several examples in the literature illustrate that firms are concerned with the spillover of quality knowledge at shared suppliers. For instance, Spekman and Gibbons (2008) point out that Pratt and Whitney was wary that their competitor Rolls Royce would also benefit when they improved quality at their shared supplier, Dynamic Gunver Technologies. Similarly, Handfield et al. (2006) highlight that Motorola worked with suppliers to segregate manufacturing to prevent competitors from obtaining information about how Motorola's parts are manufactured. However, little research has investigated the spillover of quality knowledge.

Several empirical studies have examined knowledge spillover across a variety of domains—R&D activity (e.g., Jaffe 1986, D'Aspremont and Jacquemin 1988), cost efficiency (e.g., Knott et al. 2009), and inventory management (e.g., Yao et al. 2012), to name a few. Empirical evidence on the spillover of knowledge has been found in many situations, such as from universities to corporations (e.g., Jaffe et al. 1993), across firms within an industry (e.g., Knott et al. 2009), across firms within a region (e.g., Alcácer and Chung 2007), and within supply chains (e.g., Cheng and Nault 2007). However, there are two broad reasons as to why these findings may not carry over to the quality domain. First, Levin (2000) demonstrates in his research that results obtained in other domains, such as cost and productivity, do not necessarily carry over to the quality domain. Second, the literature on knowledge spillovers mainly uses aggregate measures (i.e., R&D investments, economic area patent stock, overall investments in technology, etc.) to assess the development of knowledge and to evaluate spillover. These findings based on aggregate measures may be insufficient in the quality domain because the development of quality knowledge can be linked to specific actions (i.e., quality improvement initiatives), which can also facilitate a deeper investigation of the factors that affect spillover.

The literature has examined the development of quality knowledge and finds that firms can improve quality by performing the same task repeatedly (*autonomous learning*) and by undertaking conscious actions to improve quality (*induced learning*), across a variety of settings—continuous manufacturing (e.g., Lapré et al. 2000), discrete manufacturing (e.g., Ittner et al. 2001, Choo 2011), and healthcare (e.g., Nembhard and Tucker 2011). However, hardly any research has examined whether firms can benefit from the spillover of quality knowledge developed by the conscious efforts of other firms at shared suppliers. Consequently, in this study we aim to provide a deeper understanding of spillover in the quality domain by investigating the following research questions: (1) Does quality knowledge spillover at shared suppliers? and (2) What are the potential factors that govern the spillover of quality knowledge?

Our results indicate that, in general, quality knowledge is sticky and does not easily spillover to benefit other firms. Additionally, we identify three potential factors that may affect the spillover of quality knowledge. The first factor pertains to the potential reservoirs of organizational knowledge in production environments: *technology*, *routines*, and *organizational members* (Argote and Ingram 2000, Agrawal and Muthulingam 2015). When organizational knowledge can be precisely formulated and articulated (i.e., when it is *explicit knowledge*), it can be effectively embedded in technology (e.g., Nonaka and von Krogh (2009)) or it can be retained in organizational routines (e.g., Zollo and Winter 2002). In contrast, when organizational knowledge is subconsciously understood and difficult to articulate (i.e., when it is *tacit knowledge*), it is often retained with organizational members. Spillover of organizational knowledge can vary depending on whether it is embedded in technology, routines, or organizational members (Argote 2013). The literature suggests that knowledge embedded in technology or routines is likely to spillover. In contrast, we find that the quality knowledge developed through quality improvement initiatives that involve organizational members spills over, whereas the quality knowledge obtained from initiatives that focus on technology or routines does not spill over.

The second factor relates to where the quality improvement initiatives are undertaken within the supplier's manufacturing facilities. We build on Juran (1988) to identify whether the quality improvement initiatives in our data are implemented in the input, in-process, or output activities of the suppliers' value chains. Quality improvement initiatives that focus on input activities can improve quality by ensuring better inputs into the manufacturing process (including work with subsuppliers), quality efforts on in-process activities can enhance quality by ensuring manufacturing processes produce good quality parts, and quality efforts on output activities can ensure quality by identifying and removing defective parts or by improving transportation processes (Juran 1988). The differing mechanisms to improve quality performance can have differing impact on the extent to which quality knowledge spills over. We find that quality knowledge developed from quality improvement initiatives that focus on the output activities of the supplier's value chain is likely to spill over.

The third factor is linked to the complexity of operations at vendor facilities. Increased complexity in supply chains can have a detrimental effect on quality performance (e.g., Calinescu et al. 1998). This is because, complex systems make it challenging to understand how the various factors of production combine and affect quality performance. As a result, to improve quality in complex operations, firms need to develop a precise understanding of how various factors interact. Developing such an understanding may be demanding for a firm that was not directly involved with improving quality at the supplier. We find that quality knowledge spills over only at suppliers with low levels of complexity in their operations.

This paper makes several contributions. First, we explicitly examine the spillover of quality knowledge; thus we extend the literature on knowledge spillovers to the quality domain. Second, in contrast to the results in the existing literature, we find that quality knowledge obtained from initiatives that focus on technology and routines does not spill over, whereas quality knowledge obtained from initiatives that involve organizational members does spill over. Third, we find that quality knowledge gained from initiatives that focus on output activities is likely to spill over and we demonstrate the link between the complexity of operations and the spillover of quality knowledge. Thus, we add to the literature on knowledge spillovers by highlighting the impact of factors that have not been explored so far. Finally, our results are also relevant for operating managers because they provide insights on how quality improvement efforts can be managed at shared suppliers to mitigate the impact of spillover.

The rest of the paper is organized as follows. In Section 2, we describe the research setting. In Section 3, we present our hypotheses. In Section 4, we describe the data and the measures used in our analysis. In Section 5, we discuss our methodology. In Section 6, we present our results. In Section 7, we discuss the implications of our findings and the limitations of our analysis.

2. Research Setting

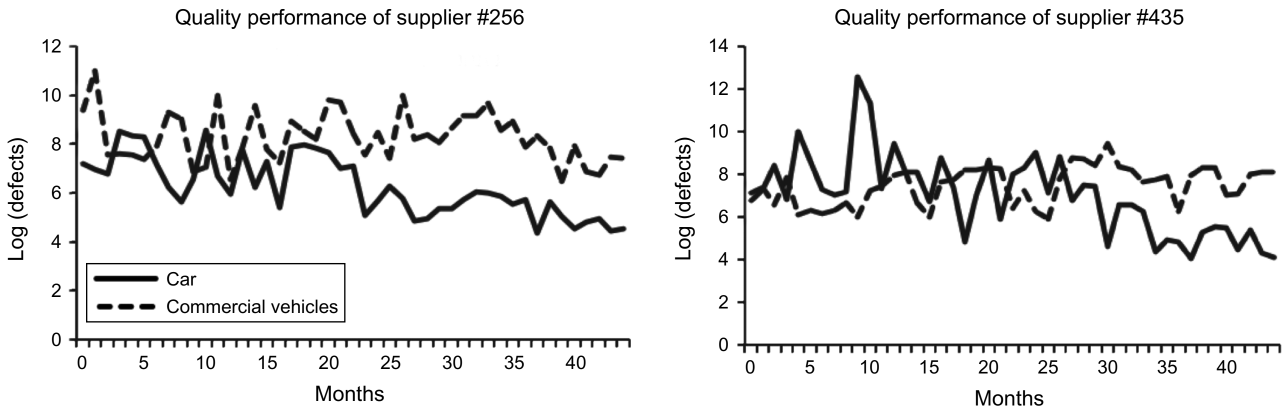
While the literature recognizes that quality knowledge can spill over, it has been challenging to measure such spillover at shared suppliers and to examine the operational contingencies that affect it. This is because in order to effectively examine the spillover of quality knowledge at suppliers, it is essential to (1) observe the quality performance of shared suppliers at different buyers, (2) identify the quality improvement efforts undertaken at the supplier facilities, and (3) obtain data on the operational factors at supplier facilities that can affect quality performance. This study uses data from a unique empirical context that overcomes these challenges.

We examine the longitudinal quality performance of the suppliers to two distinct businesses of AMC (a large automotive conglomerate who requested confidentiality): "the car business" (henceforth Car) and "the commercial vehicles business" (henceforth Commercial). These businesses are independent entities within AMC, and are managed by separate business heads with distinct organizational structures and different manufacturing facilities. Prior to 2006, both Car and Commercial used similar structures to procure components from their suppliers. Both businesses had quality departments that assessed the quality performance of the suppliers and they used a comprehensive assessment process that included incoming inspection, in-process evaluation, and final product testing. Additionally, both businesses had vendor development departments comprised of buyers who were responsible for pricing, new part development, incoming deliveries, and supply of parts to the production lines. The buyers at both businesses were organized by the technology of the sourced components. So suppliers supplying plastic components were handled by one buyer at Car, while another buyer handled suppliers supplying castings, and so forth. Buyers at Commercial were organized similarly.

In 2006, Car initiated a supplier quality improvement program by creating a separate division called the "Supplier Improvement Unit" (SIU), which consisted of engineers drawn from within the employees of Car. This division was responsible for working collaboratively with the 295 suppliers of Car to improve the quality of the parts supplied to Car. The SIU was organized so that each SIU engineer was responsible for the quality performance of 10 to 15 suppliers with similar technology. Thus, the SIU engineers were aligned with the buyers from the vendor development department of Car. The direct responsibility for a small group of suppliers enabled the SIU engineers to interact closely with the suppliers and to visit their facilities frequently. This allowed the SIU engineers and the suppliers to identify quality issues, develop solutions for quality problems, and test the proposed solutions; and these interactions facilitated the development of quality knowledge at the suppliers. Additionally, Car structured the quality improvement program such that all the benefits from the quality improvement efforts accrued to the suppliers, and the pricing of components was de-linked from the quality improvement program. This approach ensured that suppliers would collaborate with the SIU engineers and support the quality improvement efforts.

From 2006, the SIU engineers worked with the 295 suppliers of Car to develop quality improvement initiatives to address quality problems identified through Car's quality assessment process. Of these 295 suppliers, 191 suppliers used the same manufacturing facilities and production lines to supply similar components to Commercial. Sixteen SIU engineers worked with these 191 shared suppliers. As the SIU engineers were aligned with the buyers from the vendor development department of Car, 16 buyers of Car handled these 191 shared suppliers. From April 2006 to December 2009, 2,121 quality improvement initiatives were implemented at these 191 shared suppliers. Table 1 provides select examples of these initiatives. However, during this period, our discussions and interactions with the managers of Commercial as well as the managers at supplier facilities indicate that

Figure 1 **Evolution of Quality Performance of Select Suppliers**



Notes. Defects are measured in parts per million (ppm). Supplier #256 provides die castings, and supplier #435 provides pipes and flanges.

Commercial did not undertake any modifications to its sourcing setup nor did it undertake any directed quality improvement efforts at the shared suppliers.

We interacted extensively with the managers and engineers at Car, Commercial, and the shared suppliers. This allowed us to better understand the nuances of how quality knowledge gets developed and how it can spill over at shared suppliers. Figure 1 shows the quality performance (measured in terms of defect rates) of suppliers 256 and 435 who supply "die castings" and "pipes and flanges," respectively, to both Car and Commercial. We see that the quality performance of components supplied to Car improves over time for both suppliers. An engineer from Car explained how quality knowledge was developed at the suppliers: "We work with the suppliers to identify root causes and potential remedies for quality problems and this helps them to implement changes to improve the quality of components supplied to the car division. Over time the suppliers develop the capabilities to address quality problems." In comparison, the quality performance of components supplied to Commercial by supplier 256 shows some improvement (though the quality improvement is lower than that of Car), whereas the quality performance of supplier 435 shows hardly any improvement. In an interview, a senior manager at supplier 256 described how quality knowledge may spill over: "Working with Car helps us to improve our quality performance for Car, and we use similar ideas to improve quality for Commercial." In another interview, a senior manager at supplier 435 indicated that some challenges may hinder the spillover of quality knowledge: "Though we improved quality performance for Car, we are finding it challenging to use these lessons for Commercial. Even when the problems are similar, the solutions for Car are not necessarily implementable as is." These comments indicate that quality knowledge developed at the shared suppliers can spill over to benefit other buyers, however they also endorse the idea that not all of the quality knowledge developed at the suppliers will spill over.

Three features of our research setting make it attractive to analyze knowledge spillover in the quality domain. First, the components sourced by Car and Commercial are similar. A large majority of the components (78%) in our data share similar designs, though their dimensions differ. Therefore improvements made for Car's components are also likely to be relevant for Commercial's components. Second, the 191 shared suppliers in our study use common manufacturing facilities to manufacture the components for Car and Commercial. This meant that often production lines and employees were shared for the manufacture of the components for Car and Commercial. Thus, improvements made in the manufacturing processes for Car's components are also relevant for Commercial's components. These two features ensure that the operational aspects of manufacturing of the components for Car and Commercial are closely matched. Thus, they permit the investigation of operational contingencies that may govern the spillover of quality knowledge, which has not been possible in the literature so far. Finally, both businesses do not directly compete. As a result, Car did not undertake any conscious efforts to avoid the spillover of quality knowledge. Thus, our setting allows us to directly observe the spillover at the suppliers and avoids potential confounding effects that may arise if the firm took specific measures to avoid spillover.

3. Hypotheses

In our hypotheses, we first consider the spillover of quality knowledge across all the shared suppliers. Then we examine the contingencies that govern the spillover of quality knowledge.

To address quality issues effectively firms must understand potential modes of failure, identify underlying causes for failure, explore potential solutions, and implement relevant remedies to address the causes of failure (e.g., Ishikawa 1985, Deming 1986). When a firm and its' supplier work on a quality problem (e.g., temperature sensor cracks because of excess torquing, as in Example 1 in Table 1), the process of understanding the causes and implementing the appropriate solutions for the specific quality issue also helps them to develop knowledge to tackle other similar quality issues (e.g., pressure sensor cracks because of improper torquing). As the firm and the supplier work repeatedly on addressing a variety of quality issues they gain experience and develop knowledge to address a diverse range of quality issues. This essentially means that the firm and its suppliers develop quality knowledge with their cumulative quality improvement efforts (e.g., Li and Rajagopalan 1998, Lapré et al. 2000, Nembhard and Tucker 2011, Easton and Rosenzweig 2012). When suppliers also make components for other firms, some of the quality knowledge can spill over to benefit other firms because of two reasons. The first reason is that knowledge is not an appropriable commodity (Arrow 1963); once suppliers know how to manage their operations to improve quality performance it is logical that they will also use the knowledge to improve the quality

Table 1 Select Quality Improvement Initiatives Undertaken by Car

Number	Quality problem observed at car	Quality improvement initiative implemented at supplier facilities	Technology, routines, operators	Input, in-process, output	Complexity of supplier's operations
1	The adaptor of temperature sensor is getting cracked. Diagnosis: Excess torque during engine assembly.	Raw material of housing changed to rivettable brass and wall thickness increased from 1.4 mm to 3.6 mm.	Technology	Input	Medium
2	Release paper not coming out cleanly from plastic membrane of Front Door LH.	Dehumidification of LDPE granules started before processing at subsupplier's end.	Technology	Input	Low
3	In final assembly of shifting bracket, the 3 mm spring retention hole position shifted downward. Diagnosis: Reverse orientation of lever in drilling fixture.	Poka yoke: Additional stoppers incorporated in the drilling fixture to prevent fitting of components in reverse orientation in the drilling fixture, independent of the operator.	Technology	In-Process	Low
4	Core diameter out of specification in assembly bracket for FIP mounting. Diagnosis: Guide bush to check hole position is short, which results in accepting defective parts.	Inspection method improved: Guide bush length of checking pin increased from 15 mm to 22 mm.	Technology	In-Process	Medium
5	Assembly filler neck with bracket (w/o baffle), powder coating problems observed. Diagnosis: Transit damage.	Special trolley deployed for internal handling at supplier and transportation of assembly filler neck from supplier to Car.	Technology	Output	Medium
6	Turbo charger blade damage. Diagnosis: Foreign material entry from air filter to hose.	Milli-pore test started at hose supplier (a subsupplier) for sampling inspection.	Routines	Input	High
7	Vibration in assembly shroud fan and motor. Diagnosis: Improper balancing.	Process sequence changed. Balancing to be done before shroud assembly with fan and motor.	Routines	In-Process	High
8	Assembly driver seat recliner mechanism faulty. Height of the dimple lock from ratchet lever mounting face was 3.1 mm against specification of 3.6 ± 0.1 mm.	Inspection method modified. Dimple height to be checked with respect to the ratchet lever mounting face instead of individual dimple height checking.	Routines	In-Process	High
9	In door sealing rubber front RH, surface cuts observed. Diagnosis: Dust entry during extrusion.	Workspace to be cleaned before compound mixing. Training for every operator on Extruder machines.	Operator	In-Process	Low
10	Squareness measures of 0.25 observed against spec 0.1 mm in assembly bracket for FIP (rear) for boost sensor line mounting. Diagnosis: Caused in facing operation because of taper movement of cross slide because of excess wedge wear.	Operator/Process check: Wedge wear and machine alignments to be checked with records to be maintained.	Operator	In-Process	Medium
11	Bend in Shifter Shaft (5/R speed) observed up to 0.09 mm, which leads to gear shifting hard/sticky. Diagnosis: Control needed after heat treatment.	Bend now manually removed up to 0.03 mm after heat treatment on 100% basis	Operator	In-Process	High
12	In rear roof bow holes for wiring harness missing. Diagnosis: WIP mixed with finished inventory.	(1) Separate pallets for WIP and finished parts, (2) Finished parts will be tied by wire through the holes.	Operator	Output	Medium

Note. RH = right-hand side; LH = left-hand side; FIP = fuel injection pump; WIP = work in process; LDPE = low-density polyethylene.

of components they supply to other firms. The second reason is that several mechanisms, such as adopting established processes (e.g., Andristos and Tang 2014), leveraging the knowledge of employees (e.g., Singh and Agrawal 2011), and utilizing similar technology (e.g., Cheng and Nault 2007), can help firms gain from the improvements realized by other firms. When suppliers use the same manufacturing setup to make components for other firms, the improvements in the manufacturing operations, such as improved processes, modifications to technology, and enhanced operator skills, can be easily observed by the other buyers and the improvements can be readily incorporated for producing these components. Thus, the quality performance of the components manufactured for the other firms will also improve. Moreover, in our setting, a large proportion of components (78%) manufactured for Commercial are similar to those made for Car, which makes spillover likely. Thus, Commercial will benefit from the quality improvement efforts undertaken by Car at the shared suppliers. The above discussion leads to Hypothesis 1.

Hypothesis 1 (H1). *When a buyer develops quality knowledge at its shared suppliers by working with them to improve quality, some of the quality knowledge will spill over and improve the quality performance for other buyers that source from the same suppliers.*

In manufacturing settings, quality knowledge typically encompasses an understanding of how to manage and adapt the various constituents of manufacturing (e.g., equipment, routines, manpower, materials, etc.) to improve quality outcomes. Depending on the characteristics of the quality knowledge, it can be embedded in an organization's *technology, routines*, or *members* (Agrawal and Muthulingam 2015). In the second hypothesis, we examine whether spillover depends on where the quality knowledge developed to tackle quality issues gets embedded within supplier organizations.

Organizational knowledge developed to address quality issues can be explicit or tacit. When knowledge is precisely formulated and articulated, it is called explicit knowledge, whereas when knowledge is subconsciously understood and is difficult to articulate, it is called tacit knowledge (Polanyi 1966, Nonaka and von Krogh 2009). Explicit knowledge can be codified because it includes a clear understanding of the link between the actions required to execute a task and the outcomes of the task (Zollo and Winter 2002), whereas tacit knowledge cannot be easily codified (Nonaka and von Krogh 2009).

Technology can be an effective retainer for codified knowledge because the explicit link between the actions and outcomes can be effectively incorporated in production equipment, design changes, and material modifications (e.g., Zack 1999, Nonaka and von Krogh 2009). Further, technology can help the transfer of knowledge (e.g., Darr et al. 1995, Epple et al. 1996) and the sharing of best practices across different production facilities (Argote and Darr 2000). This is because when organizations use similar production equipment and incorporate the changes in design or material at other production facilities, they can replicate productivity gains achieved in one part of the organization to other parts of the organization (Epple et al. 1996). Moreover, Argote and Ingram (2000) point out that when knowledge is embedded in technology, it eases spillover to other organizations. In our context, since the suppliers use the same facilities to make similar components for Car and Commercial, the improvements made for Car are also likely to improve the quality for Commercial. Consequently, we expect the quality knowledge developed from quality improvement initiatives that focus on technology will spill over and benefit Commercial.

In manufacturing settings, routines can retain codified knowledge because they establish stabilized work patterns in response to specific stimuli to provide desired outcomes (Zollo and Winter 2002). For instance, in Example 7 of Table 1, the quality problem of vibration in the fan and motor assembly was addressed by changing the sequence of manufacturing operations, which meant that the quality knowledge was embedded in a redesigned work pattern. In our context, when the modified work patterns developed by Car are also used for the production of the components for Commercial, the quality for Commercial is likely to improve. However, Feldman and Pentland (2003) point out that routines can have a flexible component (the performative aspect) that may be subject to improvisation by agents. As a result, routines are susceptible to modifications over time. In our setting, the new routines (developed by Car) used by Commercial could be susceptible to improvisation and modification because it is unlikely that the Commercial buyers will insist on adherence to the new work patterns. Consequently, the benefits from the adoption of new work patterns developed by Car may not be completely realized by Commercial. Based on these reasons, we expect that the quality knowledge developed from quality improvement initiatives that focus on routines will spill over. However, as routines are susceptible to modifications (unlike technology focused initiatives), we expect that the spillover for routines will be less than that for technology.

The literature recognizes that organizational members can effectively acquire and store tacit knowledge within organizations (Argote 2013). This is because individuals can capture subtle nuances involved in performing tasks that may be difficult to articulate and can acquire task-specific skills through job related training (see Examples 9–12 in Table 1). However, studies have shown that it is challenging to transfer knowledge embedded in organizational members. For example, Argote et al. (1990) find that knowledge developed by shipyard workers did not translate by job rotation to other yards. Moreover, knowledge held by organizational members can be lost when individuals leave the organization or when individuals are transferred (e.g., Narayanan et al. 2009). Additionally, studies show that knowledge embedded in individuals can decay even in the absence of personnel turnover and transfers (e.g., Weldon and Bellinger 1997, David and Brachet 2011). These reasons suggest that it will be challenging to transfer knowledge through organizational members. Consequently, spillover of the quality knowledge developed by quality improvement initiatives that focus on organizational members will be low. It must be noted that some of the factors that affect the transfer of knowledge through organizational members are also relevant for the transfer of knowledge embedded in routines, however the impact of these factors on routines will be lower because routines are often documented as work instructions. Hypothesis 2 is based on the above discussion.

Hypothesis 2 (H2). *Spillover of quality knowledge will be higher for quality improvement initiatives focused on technology than for quality improvement initiatives focused on routines or on organizational members.*

In his classic work on planning for quality, Juran (1988) conceptualizes organizations as entities that receive inputs, runs processes, and provide outputs. Similar conceptualization has been used in studies across several fields (e.g., Panzar and Willig 1981, Van de Ven and Huber 1990, Kingsman 2000) and variations of this conceptualization have been incorporated in quality management methods, such as total quality management and Six Sigma, to facilitate analysis of organizational processes (e.g., Hendricks and Kelbaugh 1998). We use Juran's (1988) conceptualization to examine the spillover of quality knowledge from quality improvement efforts undertaken in the input, in-process, and output activities of suppliers. The spillover of quality knowledge can differ for quality improvement efforts that target the input, in-process, or output activities because the mechanisms that drive quality improvement can vary across these activities. Quality efforts on input activities improve quality by ensuring better inputs for manufacturing (including work with subsuppliers), quality efforts on in-process activities enhance quality by ensuring manufacturing processes produce good quality parts, and quality efforts on output activities ensure quality by identifying and removing defective parts or by improving transportation processes (Juran 1988).

Although the literature has examined the aggregate spillover of knowledge across firms, spillover of knowledge developed within specific parts of a firm has remained relatively unexplored. Consequently, to predict spillover across input, in-process, and output activities of suppliers, we turn to the literature on knowledge transfers that examines the flow of knowledge. This literature suggests that knowledge can be considered as a recipe, and that actors search among many potential options to identify new and better alternatives (Nelson and Winter 1982). Once knowledge has been developed in a specific setting it needs to be transferred to use it effectively in another setting. This means that the recipe needs to be transferred to the new setting; however, such transfers can be hindered because of imperfections in the transfer process or because of differing conditions at the recipient entity. Thus, when quality knowledge is developed to solve quality issues for one entity (Car), the complete knowledge may not be effectively available to solve similar quality issues for other entities (e.g., Commercial). Therefore, to successfully acquire knowledge, the recipient entity will need to actively search based on an imperfect recipe to build and recreate the knowledge. Furthermore, imperfections in the transfer of knowledge are likely to increase when entities are not close the source of knowledge. This implies that proximity to the source of knowledge can help entities to start with a recipe closer to the original and absorb knowledge effectively (Sorenson et al. 2006). These ideas are also aligned with the findings that firms benefit from their proximity to locations of knowledge activity (e.g., Shaver and Flyer 2000, Alcácer and Chung 2007). In our context, buyers at Commercial in their regular procurement activities interact with the transportation, final testing, and final assembly processes of suppliers, which comprise the output related activities at suppliers. This means that these buyers are closer to output activities, which makes it likely for them to absorb quality knowledge developed in these activities. For instance, in Example 5 of Table 1, the powder coating problem for the assembly filler neck was addressed by developing a special trolley to transport the components from the supplier to Car. Buyers at Commercial can easily observe these changes and incorporate them to avoid similar quality issues. By contrast, buyers at Commercial do not regularly interact with either the material procurement and subsupplier management that comprise the input related activities or the manufacturing operations that comprise the in-process activities of the suppliers. Thus, buyers at Commercial are further removed from these activities, which makes it unlikely for them to absorb the quality knowledge developed in the input and in-process activities. For instance, in Example 4 of

Table 1, the quality problem of faulty core diameter dimension was addressed by modifying an inspection tool used in one part of the manufacturing process. As buyers at Commercial do not monitor all the steps of the suppliers' manufacturing process in their regular procurement activities, it is less likely that they will observe these changes and incorporate them. The above discussion leads to Hypothesis 3.

Hypothesis 3 (H3). *Quality knowledge developed from quality improvement efforts done for output activities will exhibit higher spillover compared to those for in-process and input activities.*

The link between complexity and quality performance has been explored in several studies. It has been shown that as complexity increases quality performance decreases (Huang and Inman 2010) and process reliability deteriorates (Calinescu et al. 1998). In the context of supply chains, Novak and Eppinger (2001) find that quality performance of outsourced components decreases with increased complexity. However, little research has examined how complexity affects the spillover of quality knowledge.

Complexity can affect the spillover of quality knowledge in two ways. First, complexity can inhibit knowledge outflows. Cassiman and Veugelers (2002, 2006) find that product and process complexity helps firms avoid knowledge outflows and prevents other firms from obtaining benefits from possible knowledge outflows. Second, complexity can make it difficult for organizations to replicate capabilities. This is because complexity increases the challenges involved in understanding how various factors can combine and contribute to the development of specific capabilities (King 2007). When organizations do not have a clear understanding of the factors that support specific capabilities, their ability to replicate capabilities is hampered (Lippman and Rumelt 1982, Szulanski 1996). For instance, Rivkin (2001) shows using an agent-based simulation model that complex systems are resistant to replication. Overall, the literature indicates that knowledge transfers and the replication of capabilities are more difficult in complex operations. In our setting, when suppliers resolve quality problems for Car, they understand how various operational factors can contribute to quality problems and they develop knowledge on how to modify the relevant manufacturing elements to address the quality issues. To use this knowledge and capabilities for Commercial, suppliers must be able to (1) transfer this knowledge to the manufacturing for Commercial and (2) replicate the capabilities to effectively address the quality problems for Commercial. When the complexity of operations at suppliers is low, it will be easier to understand how various factors contribute to the resolution of quality issues and Commercial can absorb the quality knowledge developed at the suppliers by Car. By contrast, as the complexity of operations at suppliers increases, it will be more challenging to understand the link between actions and outcomes which will make it difficult for Commercial to absorb the quality knowledge developed by Car. Hypothesis 4 is based on these considerations.

Hypothesis 4 (H4). *Spillover of quality knowledge at shared suppliers will be the higher for suppliers with lower complexity in their operations.*

4. Data and Measures

4.1. Data Used for the Analysis

Our analysis uses information on 191 shared suppliers that provide components to both Car and Commercial. The data were collected for 45 months from April 2006 to December 2009. The data includes information on (1) the monthly quality performance of these suppliers for both the businesses and (2) all 2,121 quality improvement initiatives undertaken at the suppliers. Note that in our data 93 of the 191 suppliers made supplies every month in the 45-month period, and the remaining 98 suppliers made supplies for at least 30 months of the study period. In this period, the average quality performance of the suppliers improved by 83.19% and 11.97% for Car and Commercial, respectively. We supplemented the data with multiple visits to Car, Commercial, and the suppliers, spending more than 17 weeks at their facilities. We conducted 32 semistructured interviews with managers of Car and Commercial, and 29 semistructured interviews with senior personnel at some of the 191 shared suppliers.

4.2. Measures Used for the Analysis

The main variables used in our analysis pertain to measures of supplier quality performance and organizational experience. Next, we describe these variables and the controls used in our analysis.

4.2.1. Dependent Variable. *Defect Rate*—We measure supplier quality performance using monthly defect rates. For Car, the defect rate (YC_{it}) for supplier i in period t is the defective parts per million (ppm) received from supplier i in period t, and is calculated as $[(\sum_{j=1}^{n} \textit{Number of Defective Parts}_j)/(\sum_{j=1}^{n} \textit{Total Parts Supplied}_j)] \times 10^6$, where n represents the number of distinct products supplied by the supplier. Defect rate (YR_{it}) for Commercial is defined analogously. Our measure for defect rate is consistent with the literature (e.g., Ittner et al. 2001). Moreover, both businesses used this measure to evaluate supplier quality performance over the course of the study.

4.2.2. Variable to Evaluate the Overall Impact of Spillover. *Lagged Cumulative Quality Improvement Experience*—We measure this as $Q_{i(t-1)} = \sum_{t=0}^{t-1} q_{it}$, where q_{it} is the number of quality improvement initiatives implemented at supplier i in period t. Our approach to assess the impact of quality improvement initiatives using a count variable is consistent with the literature (e.g., Lapré et al. 2000, Nembhard and Tucker 2011). The quality improvement initiatives were initiated by Car, and hence the spillover of quality knowledge to Commercial can be measured by estimating the impact of these quality improvement initiatives on the defect rate for products sourced by Commercial.

4.2.3. Variables to Evaluate the Impact of Where Quality Knowledge Gets Embedded. To evaluate Hypothesis 2, we identify the quality improvement initiatives in our data based on whether they focus on technology, routines, or organizational members. An initiative was assigned to the "Technology" category if it addressed quality issues by introducing new equipment, making modifications to existing equipment, or making changes to materials or to design (see Examples 1–5 in Table 1). Initiatives that focused on changes to repetitive patterns of work or introduced new repetitive activity (see Examples 6–8 in Table 1) were identified as "Routines" (following Nelson and Winter 1982). Initiatives that addressed quality issues primarily by seeking to develop or improve operator skills (see Examples 9–12 in Table 1) were termed "Operator."

Classification began by having Car's vendor development and quality chiefs jointly choose three initiatives that fit each of the three categories: "Technology," "Routines," and "Operator." These nine examples served as the basis on which six SIU engineers undertook the classification of the 2,121 initiatives. The two chiefs then validated the resulting classification, independently. The kappa statistic of interrater agreement between these two raters is 0.73, which indicates substantial agreement (Landis and Koch 1977). Together, the two chiefs resolved any disagreements. The result—1,027 initiatives classified as "Technology," 821 as "Routines," and 273 as "Operator"—enabled us to decompose the measure of induced learning Q_{it} into three components to form the independent variables to evaluate Hypothesis 2.

Lagged Cumulative Technology—We calculate this as $E_{i(t-1)} = \sum_{t=0}^{t-1} e_{it}$, where e_{it} is the number of "Technology" initiatives implemented at supplier i in period t.

The variables *Lagged Cumulative Routines* ($R_{i(t-1)}$) and *Lagged Cumulative Operator* ($O_{i(t-1)}$) are defined analogously.

4.2.4. Variables to Evaluate the Impact of Initiative Location on Spillover. To evaluate Hypothesis 3, we identify quality improvement initiatives that are undertaken in the input, in-process, and output activities of suppliers. An initiative was identified as "Input" if it addressed quality issues by making modifications to the material procurement or subsupplier management processes (see Examples 1, 2, and 6 in Table 1). Initiatives that addressed quality issues by making modifications to the transportation, final testing, and final assembly process at suppliers (see Examples 5 and 12 in Table 1) were classified as "Output." The remaining initiatives that focus on manufacturing processes within the suppliers operations (see Examples 3, 4, and 7–11 in Table 1) were identified as "In-Process." The mapping of the quality improvement initiatives to the input, in-process, and output activities was done by the SIU engineers and validated by the vendor development and the quality chiefs of Car independently. The kappa statistic of interrater agreement is 0.77, which indicates substantial agreement (Landis and Koch 1977). In our data, 484, 1,161, and 476 quality improvement initiatives were focused on input, in-process, and output activities, respectively. This classification enables us to decompose the measure of induced learning Q_{it} into three components to form the independent variables to evaluate Hypothesis 3:

Lagged Cumulative Input—We calculate this as $IN_{i(t-1)} = \sum_{t=0}^{t-1} in_{it}$, where in_{it} is the number of quality improvement initiatives pertaining to input activities implemented at supplier i in period t.

The variables *Lagged Cumulative In-Process* ($IP_{i(t-1)}$) and *Lagged Cumulative Output* ($OP_{i(t-1)}$) are defined analogously.

4.2.5. Variable to Evaluate the Impact of Complexity on Spillover. We measure the complexity of supplier operations (C_{it}) based on two factors: product complexity and manufacturing complexity. Next, we provide a brief overview of our approach to measure complexity, but defer a more comprehensive discussion on this to Appendix A (available as supplemental material at http://dx.doi.org/10.1287/msom.2016.0585). We adopt the approach used by Novak and Eppinger (2001) and evaluate product complexity on a spectrum of 0 to 1 (low product complexity to high product complexity) as the average of three characteristics: (1) the number of subcomponents of a product, (2) product interactions, and (3) product novelty, each of which are scaled from 0 to 1. Manufacturing complexity is evaluated based on discussions with the SIU team as the average of two features: (1) the tolerance limits required for the product and (2) the sophistication involved in the manufacturing process, each of which are scaled from

0 to 1. Then, we calculate complexity of supplier operations as

$$\textit{Complexity of supplier operations } (C_{it}) = \frac{1}{n}\sum_{i=1}^{n}\frac{\textit{product complexity}_i + \textit{manufacturing complexity}_i}{2},$$

where "n" represents the number of distinct products sourced from each supplier. The SIU engineers computed the complexity scores for each of their respective suppliers. These scores were then validated with the vendor development and quality chiefs at Car independently. In our data, the complexity of supplier operations C_{it} ranged from 0.2 (low complexity) to 1 (high complexity), with a mean of 0.69 and a standard deviation of 0.18; and we use this measure to evaluate Hypothesis 4. (Note that complexity for Commercial is similar to that for Car because of the signifcant overlap in sourcing. Therefore, we only use complexity calculated for Car in our analyses.)

4.2.6. Controls. *Cumulative Production Experience*—We control for the fact that quality performance of the products supplied to Car and Commercial can improve with the respective production volumes because of learning-by-doing (Li and Rajagopalan 1998, Gray et al. 2009). For Car, we capture the effect of learning-by-doing by using "lagged cumulative production volume ($PC_{i(t-1)}$)," which is measured as $PC_{i(t-1)} = \sum_{t=0}^{t-1} pc_{it}$, where pc_{it} is the number of units (in 100,000) supplied by supplier i in period t. The start of our time series coincides with the introduction of the quality improvement initiatives, and therefore we assume that $pc_{i0} = 0$. Lapré and Tsikriktsis (2006, p. 356) state "…for the exponential form (of the learning curve), accounting for prior experience is a nonissue—omission of prior experience will *not* bias learning-rate estimates." So, we use the exponential form of the learning curve because we do not observe the complete history of production experience. Similarly for Commercial, we define "lagged cumulative production volume ($PR_{i(t-1)}$)" to capture the effect of learning-by-doing.

Supplier Random Effects—We control for supplier related characteristics that may affect quality performance by using supplier-level random effects. The Hausman test for fixed versus random effects indicates that the supplier random effects model is the appropriate model ($p < 0.01$).

SIU Engineer Controls—We use indicator variables to identify the specific SIU engineer from Car associated with each supplier. This allows us to control for SIU engineer specific factors which could affect Car's interactions with the suppliers. Additionally, since the SIU engineers handle suppliers with similar technology (such as plastics, forgings, castings, etc.), the indicator variables also control for time-invariant factors such as technology. Furthermore, the organization of the SIU engineers was aligned with the buyers of the vendor development department, hence these variables also control for the impact of the specific buyers at Car. (Note that SIU Engineer indicators are also highly correlated with the buyer level indicators for Commercial becasue the organization of buyers between Car and Commercial was similar. Thus separate indicators for Commercial buyers were not feasible in our models.)

Product Mix and Model Controls—From 2006 to 2009, Car manufactured two to four types of car every month and experienced three model changes. In line with Thompson (2007), we control for these changes by using indicator variables that identify whether a specific product was produced in a month or not.

Time Fixed Effects—We use indicator variables that identify the year pertaining to our data. These control for potential factors that may change over time.

Tables 2 and 3 provide the descriptive statistics and correlations for our data. From Table 2, we see

Table 2 Descriptive Statistics

	Mean	Standard deviation	Minimum	Maximum
(1) Log (defects)—Car	*			
(2) Log (defects)—Commercial vehicles	*			
(3) Quality improvement initiatives	0.247	1.23	0.00	24.00
(4) Quality improvement initiatives—Technology	0.121	0.54	0.00	17.00
(5) Quality improvement initiatives—Routines	0.094	0.60	0.00	13.00
(6) Quality improvement initiatives—Operator	0.032	0.33	0.00	8.00
(7) Quality improvement initiatives in input activites	0.057	0.41	0.00	6.00
(8) Quality improvement initiatives in in-process activities	0.136	0.66	0.00	24.00
(9) Quality improvement initiatives in output activities	0.055	0.39	0.00	11.00
(10) Production experience—Car	2.080	10.95	0.00	198.00
(11) Production experience—Commercial	1.350	7.86	0.00	201.00
(12) Complexity	0.690	0.18	0.21	1.00

*To protect AMC's proprietary information, we do not report descriptive statistics for defects.

Table 3 Correlations

	Correlations											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Log (defects)—Car	1.00											
(2) Log (defects)—Commercial	—	1.00										
(3) Lagged cumulative quality improvement experience	**−0.18**	**0.03**	1.00									
(4) Lagged cumulative technology	**−0.12**	**0.05**	—	1.00								
(5) Lagged cumulative routines	**−0.17**	**−0.02**	—	**0.58**	1.00							
(6) Lagged cumulative operators	**−0.16**	**−0.04**	—	**0.44**	**0.37**	1.00						
(7) Lagged cumulative input	**−0.13**	**0.02**	—	**0.11**	**0.11**	**0.12**	1.00					
(8) Lagged cumulative in-process	**−0.17**	**−0.01**	—	**0.24**	**0.08**	**0.11**	**0.61**	1.00				
(9) Lagged cumulative output	**−0.15**	**0.02**	—	**0.12**	**0.14**	**0.07**	**0.39**	**0.43**	1.00			
(10) Lagged cumulative production experience—Car	**−0.21**	—	**0.16**	**0.11**	**0.20**	**0.14**	**0.14**	**0.18**	**0.10**	1.00		
(11) Lagged cumulative production experience—Commercial	—	**−0.14**	**0.08**	**0.01**	**0.09**	**0.05**	**0.06**	**0.12**	**0.04**	—	1.00	
(12) Complexity	**−0.05**	**−0.09**	**0.03**	**−0.01**	**−0.02**	**−0.01**	**−0.01**	**−0.01**	**−0.02**	**−0.01**	**−0.04**	1.00

Note. Bold denotes significance at less than 5%.

that on average 0.247 quality improvement initiatives were implemented at a supplier in a month. Additionally, every month on average each supplier provided Car and Commercial with 208,094 and 135,013 components, respectively. Further, Table 3 indicates that quality improvement experience and production experience are negatively correlated with defect rates for Car. However, for Commercial, not all constituents of quality improvement experience are negatively correlated with defect rates.

5. Methodology

We start by investigating models that examine the overall development and spillover of quality knowledge. Then, we use separate models to study the impact of potential contingencies on the spillover of quality knowledge. Finally, we investigate the combined impact of the various contingencies in a single model. All analyses were done with STATA (version 13).

5.1. Models to Evaluate the Overall Development of Quality Knowledge and Its Spillover

A large body of work highlights that quality knowledge can be developed through conscious efforts such as implementing quality improvement initiatives (*induced learning*) and through production experience (*autonomous learning*) (e.g., Lapré et al. 2000, Nembhard and Tucker 2011). We leverage this literature to examine whether quality knowledge is developed at the shared suppliers as they work with Car. Consequently, we represent the suppliers' quality performance (i.e., defect rate—YC) for Car as a function of quality improvement experience (Q) and production experience (PC) using the following specification:

$$\ln(YC_{it}) = \alpha_{ci} + \beta_{ci} Q_{i(t-1)} + \gamma_{ci} PC_{i(t-1)} + \zeta_{ci} C_i + \eta_{ci} S_i + \phi_{ci} Z_t + \epsilon_{cit}. \tag{1a}$$

In specification (1a), the terms YC_{it}, $Q_{i(t-1)}$, and $PC_{i(t-1)}$ are as described in Section 4.2; C_i represents the complexity of supplier operations; S_i represents supplier random effects; $\mathbf{Z}_t$ represents a vector of controls that includes product mix controls, SIU Engineer controls, and time fixed effects; and ϵ_{cit} represents the error terms. Here, β_{ci} denotes the learning rate for quality improvement experience, and γ_{ci} denotes the learning rate for production experience. If learning contributes to the development of quality knowledge, then β_{ci} and γ_{ci} will be significant and negative.

A core idea in specification (1a) is that quality improvement experience creates quality knowledge, which in turn improves quality performance. However, the knowledge gained from quality improvement experience is latent because specification (1a) only relates quality improvement experience to quality outcomes. To investigate the spillover of quality knowledge, we need an estimate of the learning that manifests from the quality improvement experience. This is because what spills over is the knowledge gained from experience and not just the experience. To this end, we estimate a modified specification for the suppliers' quality performance without the quality improvement experience, as shown below:

$$\ln(YC_{it}) = \alpha'_{ci} + \gamma'_{ci} PC_{i(t-1)} + \zeta'_{ci} C_i + \eta'_{ci} S_i + \phi'_{ci} Z_t + \epsilon'_{cit}. \tag{1b}$$

Note that the prediction of log defect rates (i.e., $[\ln(\widehat{YC}_{it})]_{1b}$) based on specification (1b) does not include the impact of the quality improvement experience. Whereas similar prediction based on specification (1a) includes the impact of the quality improvement experience. Therefore, the difference between these predicted values represents the manifestation of "learning from quality improvement experience (Δ_{it})," and is computed as $\Delta_{it} = [\ln(\widehat{YC}_{it})]_{1a} - [\ln(\widehat{YC}_{it})]_{1b}$. This allows us to estimate the spillover of quality knowledge to Commercial using the following specification:

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{ri}\Delta_{it} + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (1c)$$

In specification (1c), the terms YR_{it} and $PR_{i(t-1)}$ are as described in Section 4.2, ϵ_{rit} represents the error terms, and the other terms are as described in specification (1a). Here, β_{ri} denotes the learning rate for Commercial because of the quality improvement efforts undertaken by Car. If quality knowledge spills over to benefit Commercial, then we expect that β_{ri} will be significant and negative. We estimate specifications (1a) and (1c) using panel data regression. We use clustered standard errors in our analyses in line with Wooldridge (2002, p. 311) to account for the fact that our data exhibit within-panel serial correlation (Note that estimating specifications (1a) and (1c) assuming errors arise from an AR(1) process provides similar results.) These results are shown in columns (L1) and (L2) of Table 4.

5.2. Models to Examine the Individual Impact of the Contingencies on Spillover

We now examine the three potential contingencies that govern the spillover of quality gains. First, we examine how spillover is affected by where quality knowledge gets embedded. We modify specification (1a) to include variables for lagged cumulative technology ($E_{i(t-1)}$), lagged cumulative routines ($R_{i(t-1)}$), and lagged cumulative operator ($O_{i(t-1)}$) to obtain the following specification:

$$\ln(YC_{it}) = \alpha_{ci} + \beta_{ciE} E_{i(t-1)} + \beta_{ciR} R_{i(t-1)} + \beta_{ciO} O_{i(t-1)} + \gamma_{ci} PC_{i(t-1)} + \zeta_{ci} C_i + \eta_{ci} S_i + \phi_{ci} Z_t + \epsilon_{cit}. \quad (2a)$$

In specification (2a), we expect the coefficients of induced learning ($\beta_{ciE}, \beta_{ciR}, \beta_{ciO}$) to be significant and negative, indicating that quality improvement initiatives that focus on technology, routines, and operators contribute to improved quality performance for Car.

To estimate the learning that could manifest from the specific experience related to technology, routines, and operators, we modify specification (2a) by excluding the quality experience related to technology, routines, and operators, one at a time, to obtain the following three specifications:

$$\ln(YC_{it}) = \alpha'_{ci} + \beta'_{ciR} R_{i(t-1)} + \beta'_{ciO} O_{i(t-1)} + \gamma'_{ci} PC_{i(t-1)} + \zeta'_{ci} C_i + \eta'_{ci} S_i + \phi'_{ci} Z_t + \epsilon'_{cit}; \quad (2b)$$

$$\ln(YC_{it}) = \alpha'_{ci} + \beta'_{ciE} E_{i(t-1)} + \beta'_{ciO} O_{i(t-1)} + \gamma'_{ci} PC_{i(t-1)} + \zeta'_{ci} C_i + \eta'_{ci} S_i + \phi'_{ci} Z_t + \epsilon'_{cit}; \quad (2c)$$

$$\ln(YC_{it}) = \alpha'_{ci} + \beta'_{ciE} E_{i(t-1)} + \beta'_{ciR} R_{i(t-1)} + \gamma'_{ci} PC_{i(t-1)} + \zeta'_{ci} C_i + \eta'_{ci} S_i + \phi'_{ci} Z_t + \epsilon'_{cit}. \quad (2d)$$

Then, the manifestation of "learning from technology related experience (Δ_{Eit})" is the difference between the predicted values of log defect rates between Equations (2a) and (2b), and is calculated as $\Delta_{Eit} = [\ln(\widehat{YC}_{it})]_{2a} - [\ln(\widehat{YC}_{it})]_{2b}$. The manifestation of "learning from routines related experience (Δ_{Rit})" and "learning from operator related experience (Δ_{Oit})" are calculated similarly as

$$\Delta_{Rit} = [\ln(\widehat{YC}_{it})]_{2a} - [\ln(\widehat{YC}_{it})]_{2c}$$

and

$$\Delta_{Oit} = [\ln(\widehat{YC}_{it})]_{2a} - [\ln(\widehat{YC}_{it})]_{2d},$$

respectively. The corresponding spillover of quality knowledge to Commercial can now be estimated using the following specification:

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{riE}\Delta_{Eit} + \beta_{riR}\Delta_{Rit} + \beta_{riO}\Delta_{Oit} + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (2e)$$

If quality knowledge spills over to benefit Commercial, then the coefficients of learning from the specific quality experience ($\beta_{riE}, \beta_{riR}, \beta_{riO}$) in specification (2e) will be significant and negative. Moreover, in line with Hypothesis 2, we expect that ($\beta_{riE} < \beta_{riR}, \beta_{riO}$) indicating that quality knowledge developed from quality efforts that focus on technology will spill over more than the knowledge developed from efforts that focus on routines and operators.

Second, we examine whether spillover depends on where the quality improvement efforts are undertaken in the suppliers' value chain. We modify specification (1a) by using variables that identify the quality improvement initiatives undertaken in the input ($IN_{i(t-1)}$), in-process ($IP_{i(t-1)}$), and output ($OP_{i(t-1)}$) activities of the suppliers' value chain to obtain the following specification for Car:

$$\ln(YC_{it}) = \alpha_{ci} + \beta_{ciIN} IN_{i(t-1)} + \beta_{ciIP} IP_{i(t-1)} + \beta_{ciOP} OP_{i(t-1)} + \gamma_{ci} PC_{i(t-1)} + \zeta_{ci} C_i + \eta_{ci} S_i + \phi_{ci} Z_t + \epsilon_{cit}. \quad (3a)$$

We expect the coefficients of induced learning (β_{ciIN}, β_{ciIP}, β_{ciOP}) to be significant and negative, indicating the presence of learning effects for Car.

To determine the spillover from the initiatives originating at these three places in the suppliers' value chain, we use the approach adopted to develop specification (2e) and obtain the following specification:

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{riIN}\Delta_{INit} + \beta_{riIP}\Delta_{IPit} + \beta_{riOP}\Delta_{OPit} + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (3b)$$

In the above specification, Δ_{INit}, Δ_{IPit}, and Δ_{OPit} represent the manifestation of learning that can be assigned

Table 4 Estimation Results to Examine the Spillover of Quality Knowledge (Hypotheses 1 to 4)

Dependent variable: Log (defect rate)	Overall models (H1)		Technology, routines, operator (H2)		Input, in-process, output (H3)		Complexity of supplier operations (H4)	
	(L1)	(L2)	(L3)	(L4)	(L5)	(L6)	(L7)	(L8)
Hypothesis 1								
Lagged cumulative quality improvement experience (β_{ci});	−0.0413***	−0.1875					−0.0449***	−0.1557
Learning from quality improvement experience (β_{ri})	(0.007)	(0.161)					(0.007)	(0.173)
Hypothesis 2								
Lagged cumulative technology (β_{ciE});			−0.0261**	0.0752				
Learning from technology related experience (β_{riE})			(0.010)	(0.043)				
Lagged cumulative routines (β_{ciR});			−0.0390**	−0.1087				
Learning from routines related experience (β_{riR})			(0.014)	(0.061)				
Lagged cumulative operator (β_{ciO});			−0.0510**	−0.2754*				
Learning from operator related experience (β_{riO})			(0.023)	(0.121)				
Hypothesis 3								
Lagged cumulative input (β_{ciIN});					−0.0133**	0.4699		
Learning from experience in input activities (β_{riIN})					(0.005)	(0.326)		
Lagged cumulative in-process (β_{ciIP});					−0.0695***	−0.0921		
Learning from experience in in-process activities (β_{riIP})					(0.012)	(0.056)		
Lagged cumulative output (β_{ciOP});					−0.0348**	−0.2734*		
Learning from experience in output activities (β_{riOP})					(0.014)	(0.124)		
Hypothesis 4								
Complexity (C_i)	−0.3924***	−0.0991*	−0.3879***	−0.0744*	−0.3965**	−0.0982*	−0.4922***	−0.0863
	(0.117)	(0.048)	(0.114)	(0.037)	(0.128)	(0.045)	(0.119)	(0.065)
Quality experience · Complexity							0.0197*	0.2463*
							(0.008)	(0.105)
Controls								
Lagged cumulative production experience—Car (γ_{ci})	−0.0016***		−0.0015***		−0.0016***		−0.0015***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Lagged cum. production experience—Commercial (γ_{ri})		−0.0009***		−0.0008***		−0.0009***		−0.0008***
		(0.000)		(0.000)		(0.000)		(0.000)
Constant	6.6286***	6.6503***	6.5507***	6.5408***	6.6197***	6.6530***	6.6442***	6.6514***
	(0.117)	(0.118)	(0.121)	(0.125)	(0.117)	(0.119)	(0.110)	(0.120)
Other controls: (Supplier random effects; SIU engineer controls; Product mix and model change; Time fixed effects)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.428	0.472	0.437	0.511	0.431	0.488	0.435	0.436
N	7,458	7,458	7,458	7,458	7,458	7,458	7,458	7,458

Note. All models are significant at $p < 0.001$.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; we report coefficient estimates with cluster robust standard errors in parentheses.

to the quality improvement experience from input, in-process, and output activities, respectively. If quality knowledge spills over to benefit Commercial, then the coefficients of learning from the specific quality experience ($\beta_{riIN}, \beta_{riIP}, \beta_{riOP}$) will be significant and negative. Moreover, in line with Hypothesis 3, we expect that ($\beta_{riIN}, \beta_{riIP} > \beta_{riOP}$), which indicates that spillover will be highest for quality efforts that focus on output activities.

Third, we assess how complexity in supplier operations (C_i) affects spillover. Note that C_i is measured at the supplier level and does not change for a supplier over the period of the study. Therefore, just examining the impact of C_i in our models will not capture the impact of complexity on spillover; instead, we need to examine how C_i moderates the impact of quality experience. Consequently, we include the interaction of C_i with the measure of learning from quality experience in specifications (1a) and (1c). This results in the following modified specifications for Car and Commercial that allows us to investigate the impact of complexity on spillover:

$$\ln(YC_{it}) = \alpha_{ci} + \beta_{ci} Q_{i(t-1)} + \gamma_{ci} PC_{i(t-1)} + \zeta_{ci} C_i + \theta_{ci} Q_{i(t-1)} \cdot C_i + \eta_{ci} S_i + \phi_{ci} Z_t + \epsilon_{cit}; \quad (4a)$$

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{ri} \Delta_{it} + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \theta_{ri} \Delta_{it} \cdot C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (4b)$$

In specification (4a), we expect that the coefficient of the interaction term (θ_{ci}) will be significant and positive, which indicates that the learning from quality improvement experience will be lower for suppliers with higher complexity scores (this follows because higher values of C_i indicates higher complexity of supplier operations). Similarly, if the spillover of quality knowledge is lower for suppliers with high complexity, then we expect that the coefficient of the interaction term (θ_{ri}) in specification (4b) will be significant and positive, in line with Hypothesis 4.

We estimated the specifications (2a), (2e), (3a), (3b), (4a), and (4b) using an approach similar to the one used for specifications (1a) and (1c). These results are shown in columns (L3)–(L8), respectively, of Table 4.

5.3. Models to Examine the Joint Impact of the Contingencies on Spillover

Now, we examine the combined impact of where quality knowledge gets embedded (i.e., technology, routines, or organizational members) and where quality improvement initiatives are undertaken (i.e., input, in-process, or output activities). To do so, we modify specification (2a) to include variables for lagged cumulative input ($IN_{i(t-1)}$), lagged cumulative in-process ($IP_{i(t-1)}$), and lagged cumulative output ($OP_{i(t-1)}$) to obtain the following specification for Car:

$$\ln(YC_{it}) = \alpha_{ci} + \beta_{ciE} E_{i(t-1)} + \beta_{ciR} R_{i(t-1)} + \beta_{ciO} O_{i(t-1)} + \beta_{ciIN} IN_{i(t-1)} + \beta_{ciIP} IP_{i(t-1)} + \beta_{ciOP} OP_{i(t-1)} + \gamma_{ci} PC_{i(t-1)} + \zeta_{ci} C_i + \eta_{ci} S_i + \phi_{ci} Z_t + \epsilon_{cit}. \quad (5a)$$

In specification (5a), we expect the coefficients of induced learning ($\beta_{ciE}, \beta_{ciR}, \beta_{ciO} \beta_{ciIN}, \beta_{ciIP}, \beta_{ciOP}$) to be significant and negative, indicating the presence of learning effects for Car.

To examine the spillover of quality knowledge at Commercial, we use the approach adopted to develop specification (2e), and obtain the following specification:

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{riE} \Delta_{Eit} + \beta_{riR} \Delta_{Rit} + \beta_{riO} \Delta_{Oit} + \beta_{riIN} \Delta_{INit} + \beta_{riIP} \Delta_{IPit} + \beta_{riOP} \Delta_{OPit} + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (5b)$$

In specification (5b), if β_{riE} is significant and negative then it indicates that knowledge developed by technology focused initiatives spills over and improves the quality performance for Commercial. Analogous interpretations will apply for the coefficients estimates of the other measures of induced learning.

Now, we examine the impact of all the contingencies in a single model. To this end, we augment specification (5b) by including the interaction of complexity (C_i) with each of the measures of induced learning in specification (5b). This leads to the following modified specification for Commercial:

$$\ln(YR_{it}) = \alpha_{ri} + \beta_{riE} \Delta_{Eit} + \beta_{riR} \Delta_{Rit} + \beta_{riO} \Delta_{Oit} + \beta_{riIN} \Delta_{INit} + \beta_{riIP} \Delta_{IPit} + \beta_{riOP} \Delta_{OPit} + \theta_{riE} \Delta_{Eit} * C_i + \theta_{riR} \Delta_{Rit} * C_i + \theta_{riO} \Delta_{Oit} * C_i + \theta_{riIN} \Delta_{INit} * C_i + \theta_{riIP} \Delta_{IPit} * C_i + \theta_{riOP} \Delta_{OPit} * C_i + \gamma_{ri} PR_{i(t-1)} + \zeta_{ri} C_i + \eta_{ri} S_i + \phi_{ri} Z_t + \epsilon_{rit}. \quad (5c)$$

In specification (5c), if the coefficient of the interaction term (θ_{riE}) is significant and positive, it indicates that the spillover of quality knowledge from quality improvement experience that focuses on technology will be lower for organizations with higher complexity. Similar interpretation will apply for the coefficient estimates of other interaction terms.

We estimate the specifications (5a)–(5c), using the approach adopted for the specifications (1a) and (1c), and these results are shown in columns (L9)–(L11), respectively, in Table 5.

6. Results

In this section, we present our results and discuss several robustness tests that validate our findings.

To examine Hypothesis 1, we start by examining the development of quality knowledge. We refer to column (L1) of Table 4 and see that the coefficient of lagged cumulative quality improvement experience is negative (-0.0413) and significant ($p < 0.001$). This indicates that the suppliers' quality performance improves with cumulative quality improvement initiatives undertaken by Car and confirms the development of quality knowledge at the shared suppliers. To assess the overall impact of the quality improvement efforts (i.e., induced learning), we follow the method in Cameron and Trivedi (2009, pp. 103–104) for log-linear models of the form $\ln(\mathbf{y}) = \mathbf{x}'\boldsymbol{\beta} + \boldsymbol{\epsilon}$ and estimate the impact as $\mathbf{E}(y_i/\mathbf{x}_i) = \exp(\mathbf{x}_i'\boldsymbol{\beta})\mathbf{E}[\exp(\epsilon_i)]$. In the study period, the average number of quality improvement initiatives implemented at a supplier is 11.01 (2,121/191), therefore we estimate that induced learning reduced defect rates for Car by 70.78% (calculated as $(\hat{y}_{Q_{i(t-1)}=11.10} - \hat{y}_{Q_{i(t-1)}=0})/\hat{y}_{Q_{i(t-1)}=0} = -0.7078$).

Now, we turn to the examination of the spillover of quality knowledge. We refer to column (L2) of Table 4, for Commercial, and observe that the coefficient (β_{ri}) of "learning from quality improvement

Table 5 Estimation Results to Examine the Combined Impact on Spillover (Hypotheses 2 to 4)

Dependent variable: Log (defect rate)			
	Combined impact (without complexity interaction)		All effects in one model
	(L9)	(L10)	(L11)
Lagged cumulative technology (β_{ciE}); Learning from technology related experience (β_{riE})	−0.0582* (0.028)	0.5199 (0.349)	0.5527 (0.366)
Lagged cumulative routines (β_{ciR}); Learning from routines related experience (β_{riR})	−0.0867** (0.032)	−0.5469 (0.314)	−0.6244* (0.254)
Lagged cumulative operator (β_{ciO}); Learning from operator related experience (β_{riO})	−0.0897* (0.044)	−0.7036* (0.304)	−0.7090* (0.277)
Lagged cumulative input (β_{ciIN}); Learning from experience in input activities (β_{riIN})	−0.0349* (0.017)	−0.9403 (0.507)	−0.9636* (0.391)
Lagged cumulative in-process (β_{ciIP}); Learning from experience in in-process activities (β_{riIP})	−0.0562* (0.028)	0.3303 (0.215)	−0.3376* (0.157)
Lagged cumulative output (β_{ciOP}); Learning from experience in output activities (β_{riOP})	−0.0443** (0.015)	−0.4328* (0.207)	−0.5246 (0.333)
Complexity (C_i)	−0.3402** (0.116)	−0.0681** (0.024)	−0.1212 (0.123)
Complexity × Learning from technology related experience (θ_{riE})			0.8835* (0.407)
Complexity × Learning from routines related experience (θ_{riR})			1.0258** (0.387)
Complexity × Learning from operator related experience (θ_{riO})			1.1137* (0.432)
Complexity × Learning from experience in input activities (θ_{riIN})			1.8185** (0.637)
Complexity × Learning from experience in in-process activities (θ_{riIP})			0.5879* (0.239)
Complexity × Learning from experience in output activities (θ_{riOP})			1.4336** (0.482)
Controls			
Lagged cumulative production experience—Car (γ_{ci})	−0.0016*** (0.000)		
Lagged cum. production experience—Commercial (γ_{ri})		−0.0009*** (0.000)	−0.0008*** (0.000)
Constant	6.5489*** (0.124)	6.5314*** (0.125)	6.5358*** (0.124)
Other controls: (Supplier random effects; SIU engineer controls; Product mix and model change; Time fixed effects)	Yes	Yes	Yes
R-square	0.442	0.517	0.521
N	7,458	7,458	7,458

Note. All models are significant at $p < 0.001$.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; We report coefficient estimates with cluster robust standard errors in parentheses.

experience (Δ_{it})" is not significant. This indicates that at an overall level the quality knowledge developed at the shared suppliers does not spill over to benefit Commercial. While the overall result does not support Hypothesis 1, we defer further discussion till we examine the results for Hypotheses 2–4 on the spillover of quality knowledge under various contingencies.

For Hypothesis 2, we refer to columns (L3) and (L9) in Tables 4 and 5, respectively, for Car and confirm that the coefficients for lagged cumulative technology (−0.0261, −0.0582), lagged cumulative routines (−0.0390, −0.0867), and lagged cumulative operator (−0.0510, −0.0897) are negative and significant ($p < 0.01$, $p < 0.05$). These results confirm that quality improvement initiatives that focus on technology, routines, and operators improved quality performance for Car. Turning to columns (L4) of Table 4 and (Ll0) of Table 5 for Commercial, we see that the coefficients (β_{riE}, β_{riR}) of learning from technology and routines related experience are not significant, though the coefficients (β_{riO}) of "learning from operator related experience (Δ_{Oit})" are negative ($-0.2754, -0.7036$) and significant ($p<0.05$). Further, in columns (L4) and (Ll0), a Wald test indicates that the coefficient estimate of learning from operator related experience is significantly different from those for technology and routines related experience (i.e., $\beta_{riO} < \beta_{riE}$, β_{riR}; $p<0.05$). Thus, we infer that quality knowledge obtained from quality improvement initiatives that focus on organizational members spills over. In the study period based on the results from (L4), spillover of the quality knowledge developed through operator related experience reduced Commercial's defect rates by 4.79%. (This was calculated using the approach adopted to estimate the impact of induced learning for Car.) On the whole, these results are not aligned with Hypothesis 2.

To examine Hypothesis 3, we refer to columns (L5) of Table 4 and (L9) of Table 5 for Car and validate that the coefficients for lagged cumulative input (-0.0133, -0.0349), lagged cumulative in-process (-0.0695, -0.0562), and lagged cumulative output (-0.0348, -0.0443) are negative and significant ($p<0.01, p<0.05$). Turning to columns (L6) of Table 4 and (L10) of Table 5 for Commercial, we observe that the coefficients (β_{riOP}) of "learning from quality improvement experience in output activities (Δ_{OPit})" are negative (-0.2734, -0.4328) and significant ($p < 0.05$), whereas the coefficients (β_{riIN}, β_{riIP}) of from quality improvement experience in input and in-process activities are not significant. Further, in columns (L6) and (Ll0), a Wald test indicates that the coefficient estimate of learning from quality improvement efforts in output activities is significantly different from those for input and in-process activities (i.e., $\beta_{riOP} < \beta_{riIN}$, β_{riIP}; $p < 0.05$). In the period of our study based on the results for column (L6), quality knowledge developed through quality improvement efforts in output activities spilled over and reduced defect rates at Commercial by 3.91%. These results support Hypothesis 3.

To evaluate Hypothesis 4, we start by examining how complexity affects spillover at an aggregate level. In column (L7) of Table 4 for Car, we observe that the coefficient (θ_{ci}) of the interaction between complexity in supplier operations (C_i) and quality improvement experience ($Q_{i(t-1)}$) is positive (0.0197) and significant ($p < 0.05$), which indicates that the learning from quality improvement experience is lower for suppliers with higher complexity. Similarly, in column (L8) for Commercial, we see that the coefficient (θ_{ri}) of the interaction between complexity in supplier operations (C_i) and the "learning from quality improvement experience (Δ_{it})" is positive (0.2463) and significant ($p < 0.05$), which indicates that the spillover of quality knowledge is lower for suppliers with higher complexity.

Next, we examine how complexity affects the spillover of quality knowledge embedded in technology, routines, or organizational members and the spillover of quality knowledge obtained from quality improvement initiatives are undertaken in the input, in-process, or output activities. We refer to column (L11) and observe that the coefficient (θ_{riO}) of the interaction between complexity in supplier operations (C_i) and the induced learning measure related to operators (Δ_{Oit}) is positive (1.1137) and significant ($p < 0.05$). Additionally, the coefficient (θ_{riOP}) of the interaction between complexity in supplier operations (C_i) and the induced learning measure related to quality improvement initiatives in output activities (Δ_{OPit}) is positive (1.4336) and significant ($p < 0.01$). These results indicate that the spillover observed for initiatives that focus on operators or on output activities will be lower for suppliers with higher complexity in their operations. We also observe in column (L11) that the coefficients of the interaction between complexity and the decomposed measures of induced learning are all significant ($p < 0.05$) and positive, which indicates that complexity reduces the potential spillover of quality knowledge. Overall, these results provide support for Hypothesis 4.

Based on our results for Hypotheses 2–4, we infer that quality knowledge spills over under certain conditions, which provides partial support for Hypothesis 1. However, these results also imply that, in general, quality knowledge is sticky as it does not always spill over.

6.1. Robustness Tests

In our analyses we measure defect rates in monthly intervals. It is possible that random fluctuations in supplier defect rates observed over monthly intervals may affect the observation of spillover. To address this, we aggregated our data over two-, three-, four-, five-, and six-month intervals and repeated our analyses. Even with temporal aggregation, our results remain essentially the same.

Levin (2000) finds that quality knowledge can also develop with elapsed time. Therefore, we included an additional control for calendar time. Our results are essentially similar with this additional control.

We examined whether endogeneity is a concern in our models. In our evaluation of Hypothesis 1, if the cumulative quality improvement experience variable is mechanically related to the dependent variable of defects, it could lead to biased estimates. We addressed this endogeneity concern in two ways. First, we explored instruments for the potential endogenous variable (Wooldridge 2002) such as the cumulative quality improvement experience of other suppliers handled by the same SIU engineer and the cumulative quality improvement initiatives undertaken at other suppliers within the same industry. However, Hausman tests failed to reject the null hypothesis that cumulative quality improvement experience variable is exogenous. Second, to break the potential mechanical relationship between cumulative quality improvement experience and defect rates, we estimate specifications (1a) and (1c) with increased lags (two, three, and four months) for our experience variables. Our results remain essentially the same. The overall evidence indicates that endogeneity is not a concern in our analysis of Hypothesis 1.

To examine whether endogeneity is a concern for the evaluation of Hypotheses 2 and 3, we used the approach adopted in the context of Hypothesis 1. For example, to examine endogeneity of the decision to undertake quality initiatives that focus on technology in the context of Hypothesis 2, we explored two instruments for the potential endogenous independent variable (cumulative lagged technology): (1) the cumulative lagged technology initiatives undertaken at other suppliers handled by the same SIU engineer and (2) the cumulative lagged technology initiatives undertaken at other suppliers within the same industry. However, Hausman tests failed to reject the null hypothesis that the cumulative lagged technology initiatives variable is exogenous.

If Commercial undertook any efforts at the shared suppliers, which we did not observe, then they may account for some of our spillover results. To address this issue, we include indicators, which identify each quarter of a year, only in the regression models for Commercial. If Commercial took efforts to improve quality at a supplier in any quarter, then the indicator for the specific quarter would absorb the impact of the unobserved effort. Even with these controls, our results remain essentially the same.

We also utilized an alternative approach to examine the combined impact of all contingencies. We classified the 2,121 quality improvement initiatives using a 3×3 matrix that identifies "where quality knowledge gets embedded" on one axis and "where quality improvement initiatives are undertaken" on the other axis. The results of the multivariate regression analysis based on the above classification provide additional support for our results. Online Appendix B provides the details of this analysis.

Scholars have examined knowledge spillover by using models that estimate the impact of the experience variable of one entity on the performance of another entity (e.g., Benkard 2000, Darr et al. 1995). Along similar lines, we investigated spillover by estimating the direct impact of the quality improvement initiatives undertaken by Car on the defect rates for Commercial. Our results remain essentially the same.

7. Discussions and Limitations

This study extends the literature on knowledge spillovers to the quality domain by demonstrating the spillover of quality knowledge. Additionally, we identify three potential factors that influence such spillover. First, we find that quality knowledge embedded in organizational members spills over. In contrast, we do not find evidence for the spillover of quality knowledge embedded in technology or routines. Second, we find that quality knowledge developed in the output related activities of a supplier's value chain spills over, but quality knowledge developed in the input or in-process activities does not. Third, we show that increased complexity in operations at shared suppliers decreases the spillover of quality knowledge.

Our results naturally lead to three broad questions. First, why is spillover observed for quality knowledge developed in organizational members but not for knowledge developed in technology or routines? The reasons for these results can be traced to the fact that, in many instances, quality knowledge that gets embedded in technology and routines, may not be transparent and is consequently challenging to adopt for other products. For instance, in Example 1 of Table 1, the solution to address the sensor crack in assembly was to change the raw material of housing and to increase the thickness of the material used. The Commercial buyers may not be able to detect or perceive such changes in material thickness, which makes it challenging for them to adopt such solutions. In contrast, organizational members possess the ability to adapt and restructure knowledge so that it can be applied to new settings (Berry and Broadbent 1987) and the resulting quality gains can be sustained when they are organized in work teams (e.g., Banker et al. 2001). For instance, the solution in Example 9 of Table 1 involved operator training on cleaning the workplace before mixing raw materials. Such changes can be easily adopted and sustained for the manufacturing of products for Commercial. Consequently, quality knowledge developed in organizational members can spill over to benefit Commercial.

Second, why do quality improvement efforts undertaken in the output activities of the suppliers benefit Commercial, while improvement efforts undertaken in the input or in-process activities do not? The potential explanations for these findings can be that modifications made in the output activities of suppliers are often accessible by the Commercial buyers. For instance, in Example 12 of Table 1, the problem because of mixing of inventory was addressed by utilizing separate pallets for finished parts and work-in-process parts. The Commercial buyers can easily observe such changes and incorporate them for their parts. By contrast, changes made in the input and in-process activities are less accessible to the Commercial buyers. For instance, in Example 2 of Table 1, the problem of paper sticking to the front door handle was handled by introducing a dehumidification process at a subsupplier. Our discussions with the suppliers indicate that many times Commercial buyers did not have complete visibility on subsupplier activities, which makes it difficult for them to incorporate such changes for their parts.

Third, why does complexity mitigate spillover? Our discussions with SIU engineers indicate that when suppliers have complex operations, it is challenging for them to use the quality knowledge developed by addressing quality issues for Car to improve the quality for other products manufactured at their facilities. For instance, in Example 3 in Table 1, the problem of shifting hole position was addressed by including additional stoppers in the drilling fixture to prevent the incorrect orientation of the components for Car. However, such modifications were not straightforward for Commercial, because of the intricacies involved in identifying the appropriate positions for the stoppers and the need to simultaneously ensure the components are securely clamped on the drilling machine. In such situations, suppliers with low levels of complexity are at an advantage because the solutions for their quality issues may not be complex. This enables them to absorb the knowledge and use it, which facilitates spillover.

Additionally, it is possible that Commercial may not develop both the "know-how" and the "know-why" of addressing quality problems (Lapré et al. 2000). For instance, Commercial may develop the relevant "know-how": the need to undertake enhanced testing (e.g., modified inspection processes as in Example 8 in Table 1) or modify the relevant processes (e.g., modified process sequence as in Example 7 in Table 1), but they may lack the "know-why": the ability to identify the specific elements that need to be tested or the specific way in which they need to operate the modified processes. These factors could prevent Commercial from achieving the improved quality realized at Car.

Overall, our findings imply that quality knowledge does not spillover easily across supply chains, and that spillover occurs under specific contingencies. Therefore, when firms are concerned about spillover they must recognize that quality knowledge is likely to spillover when it is developed with operators, in the output activities, and for suppliers with low levels of complexity. Thus, in such situations, firms could avoid potential spillover by embedding quality knowledge in technology or routines and by focusing the quality improvement efforts further upstream in the suppliers operations.

Limitations of our study could be addressed in future research. First, we could not obtain reliable information on the costs incurred by suppliers for implementing the quality improvement initiatives. A future study could examine the link between the costs for implementing a quality improvement initiative and the spillover of quality knowledge. Second, we did not investigate whether the gains obtained from the spillover of quality knowledge are retained over time. This can be an interesting area for further investigation. Third, our exploration is in the automotive industry, and it remains to be seen whether our results can be generalized to other settings. Finally, we note that although field data have enriched our study, there are some inevitable limitations in field settings because not all facets of a field setting can be controlled. We hope our work will stimulate further work on the spillover of quality knowledge within supply chains.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2016.0585.

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CORRECTION

In this article, "Does Quality Knowledge Spillover at Shared Suppliers? An Empirical Investigation" by Suresh Muthulingam and Anupam Agrawal (first published in *Articles in Advance*, August 30, 2016, *Manufacturing & Service Operations Management*, DOI:10.1287/msom.2016.0585), Table 6 was included in the main text erroneously and has now been deleted.