Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Does Organizational Forgetting Affect Vendor Quality Performance? An Empirical Investigation

Anupam Agrawal, Suresh Muthulingam

MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 17, No. 3, Summer 2015, pp. 350–367
ISSN 1523-4614 (print) | ISSN 1526-5498 (online)
http://dx.doi.org/10.1287/msom.2015.0522

Does Organizational Forgetting Affect Vendor Quality Performance? An Empirical Investigation

Anupam Agrawal
Department of Business Administration, University of Illinois at Urbana–Champaign, Champaign, Illinois 61820,
aagrawal@mays.tamu.edu

Suresh Muthulingam
Smeal College of Business, The Pennsylvania State University, University Park, Pennsylvania 16802,
suresh@psu.edu

The development of organizational knowledge and the depreciation of knowledge within organizations are processes that invariably occur concurrently. In the quality domain, many researchers have examined how the development of organizational knowledge (organizational learning) enhances quality performance. We build on this literature and investigate how the depreciation of organizational knowledge (organizational forgetting) affects quality performance. We analyze information on 2,732 quality improvement initiatives implemented by 295 vendors of a car manufacturer and find that organizational forgetting affects quality gains obtained from both learning-by-doing (autonomous learning) and quality improvement initiatives (induced learning); more than 16% of quality gains from autonomous learning and 13% of quality gains from induced learning depreciate every year. Furthermore, the impact of organizational forgetting (i) differs across the types of quality improvement efforts (quality gains from process improvement initiatives depreciate, whereas those from quality assurance initiatives do not), and (ii) depends on where quality knowledge was embedded (depreciation is lower for knowledge embedded in technology than for knowledge embedded in organizational routines or organizational members). Our results highlight the ubiquity of organizational forgetting and suggest the need for continued attention to sustain and enhance quality performance in supply chains.

Keywords: quality management; process improvement; quality assurance; design quality; organizational learning; organizational forgetting; vendor management
History: Received: April 14, 2013; accepted: December 29, 2014. Published online in *Articles in Advance* April 8, 2015.

1. Introduction

With increased outsourcing of manufacturing activities, many firms have implemented programs to ensure quality in their supply chains. Despite these efforts, quality issues persist in supply chains. High profile examples include Johnson & Johnson's recall of infant medicines in 2010 due to chemical contamination from wooden pallets used by vendors (Singer and Abelson 2011) and Mattel's recall of toys in 2007 because of excessive lead in toys manufactured by vendors (Lee et al. 2008). Such quality failures have significant financial consequences: Johnson & Johnson's 2010 revenues fell by $290 million; Mattel incurred financial costs of around $110 million. What is intriguing about these examples is that further quality problems occurred after the focal firms took specific measures to avoid precisely such issues. After the 2010 recall, Johnson & Johnson's medicine division undertook a number of actions to avoid chemical contamination. But in 2011, Johnson & Johnson announced another recall after it found similar chemical contaminants in the medicines manufactured by its vendors (Johnson & Johnson 2011). Similarly, Mattel had implemented specific measures at its vendors (Early Light and Lee Der) to avoid the use of lead-based paint, yet recalls were initiated in response to lead paint in toys manufactured by the same vendors (Sodhi and Tang 2012).

These examples suggest that sometimes efforts by focal firms to improve the quality performance of their vendors may not be effective. This may be because when firms strive to develop organizational knowledge to address quality issues, they also confront the reality that knowledge within organizations can depreciate. Consequently, to ensure quality performance in supply chains, it is essential to study how supply chain quality knowledge is built, how it depreciates, and how it can most reliably be sustained. Our research focuses on these issues. We investigate how the depreciation of organizational knowledge affects vendor quality performance and examine factors that influence the impact of such depreciation.

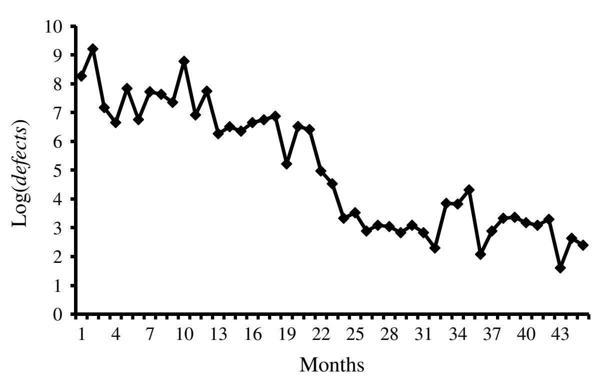
The literature has identified two mechanisms of organizational learning that facilitate quality improvement. Firms can improve quality either by performing the same task repeatedly (such learning from production experience is known as *autonomous learning*) or by undertaking conscious actions to improve quality (such learning through targeted quality improvement efforts is known as *induced learning*). An implicit assumption in this literature is that quality gains (i.e., improvements in quality performance), arising from production experience or from quality improvement initiatives, are retained over time. However, several studies find that organizational knowledge developed to reduce costs and improve productivity can depreciate because of a variety of factors, such as product changes, amendments to routines, member turnover, or equipment wear and tear. The literature refers to such depreciation of organizational knowledge as *organizational forgetting* (Benkard 2000, Argote 2013). Several scholars have mentioned that organizational forgetting may also affect quality performance (Li and Rajagopalan 1998, Lapré et al. 2000), but extant research has not explicitly examined the impact of organizational learning and organizational forgetting on quality performance. This study aims to provide a comprehensive picture of how the processes of organizational learning and organizational forgetting simultaneously impact quality performance within supply chains.

Depreciation of organizational knowledge gained from induced learning has remained relatively unexplored, but several studies have shown that cost reductions or productivity gains obtained from autonomous learning can depreciate over time (e.g., Darr et al. 1995, Benkard 2000). In some manufacturing firms, more than 90% of the cost reduction or productivity gains obtained from production experience depreciate within a year (Argote et al. 1990, Epple et al. 1996). It would be reasonable to expect that the research on the depreciation of cost and productivity gains obtained from autonomous learning will also apply to the depreciation of quality knowledge obtained from autonomous and induced learning; however, Levin (2000) provides evidence to the contrary. He investigates how the development of organizational knowledge affects quality and finds that learning depends not on production experience but on elapsed time. Therefore, we investigate how organizational forgetting affects vendor quality performance (measured in terms of defect rates) achieved through autonomous and induced learning.

This study uses data from a large automotive manufacturer in Asia that we will call "AMC" (the firm requested confidentiality). In 2006, AMC initiated a program to improve the quality performance of its vendors. AMC identified a team of engineers who worked collaboratively with the vendors to improve quality. From 2006 to 2009, 2,732 quality improvement initiatives were implemented at vendor facilities. Table 1 provides select examples of these initiatives. AMC structured the program so that the vendors retained all the benefits from the collaborative partnership. It recognized that solving quality issues involves identifying the sources of quality problems, choosing appropriate remedies to address quality issues, and working across organizational boundaries—all of which need active vendor support and buy-in. As a result, AMC developed cooperative relationships with its vendors for the quality improvement program.

We interacted closely with AMC and its vendors during this period to better understand the nuances of the quality improvement efforts. To illustrate, we refer to our interactions with a sheet metal stamping vendor whose quality performance is shown in Figure 1. We observe that the quality performance of the vendor improves over time, albeit with some variation. In an interview, a manager at the vendor attributed the quality improvement to autonomous learning: "Initially... we had quality problems, but as our workers became more familiar with producing parts with tighter tolerances for AMC, our quality levels improved." Additionally, Figure 1 also shows instances when quality gains are not sustained and quality performance depreciates. An AMC engineer elaborated on ways in which quality gains may be lost: "Sometimes people resign, key personnel go on leave, new apprentices ignore processes, or raw material suppliers change, and the vendor quality may deteriorate!" These interactions suggest that the depreciation of quality knowledge can occur even when (i) firms strive to develop quality knowledge and (ii) the focal firm and its vendors work cooperatively to enhance quality performance. The data from the quality improvement program and our interactions with AMC and its vendors enable us to examine how organizational learning and organizational forgetting affect vendor quality performance. Our thesis is that organizational learning and organizational

Figure 1 **Quality Performance of Vendor #60**



Notes. Defects are measured in parts per million (ppm). Vendor #60 supplies sheet metal stampings.

Table 1 Select Examples of Quality Improvement Initiatives Implemented at Vendors of AMC

Example	Quality problem observed at AMC	Quality improvement initiative implemented at vendor facilities	Vendor	Technology, routines, operators	Type of quality initiative
1	In rotor machining line, high rejections at profile checking station.	Inspection gauge modified for only rotary movement with no vertical movement. Fixed zero setting.	#170	Technology	Quality assurance
2	Line assembly problem with fuel injection pump in sensor mounting. Diagnosis: Inadequate guide bush length to check hole position.	Guide bush length of inspection pin increased from 15 mm to 22 mm to prevent defective parts from reaching assembly.	#59	Technology	Quality assurance
3	Improper fit of 12 H8 taper (1:8) diameter of steering knuckle with ball-pin diameter of rack and pinion joint.	Inspection gauge replaced by combination gauge. Gauge will be used for checking both 1:8 taper as well as 12H8 diameter.	#276	Technology	Quality assurance
4	Turbocharger blade damage. Diagnosis: Foreign material entry from air filter to hose.	Millipore test started at hose supplier for sampling inspection.	#201	Routines	Quality assurance
5	Assembly driver seat recliner mechanism failing. Diagnosis: Height of the dimple lock from ratchet lever mounting face was 3.1 mm against specification of 3.6 ± 0.1.	Inspection method modified. Dimple height to be checked with respect to the ratchet lever mounting face instead of individual dimple height checking.	#190	Routines	Quality assurance
6	Shift in 3 mm spring retention hole position due to reverse orientation of lever in drilling.	Poka-yoke done by incorporating stoppers in drilling fixture to prevent fitment in reverse orientation.	#10	Technology	Process improvement
7	Third and fourth gear are shifting hard during transaxle assembly testing stage.	Cup locator (∅ 19.8 mm) introduced in chamfering fixture to avoid in-process variation in wall thickness and diameter.	#82	Technology	Process improvement
8	Fuel injection pump failure. Diagnosis: Solenoid failure caused by water ingress.	Automated rotary fixture for even sealant application in solenoid manufacture.	#140	Technology	Process improvement
9	Vibration in assembly shroud fan and motor. Diagnosis: Improper balancing.	Process sequence changed. Balancing to be done before shroud assembly with fan and motor.	#99	Routines	Process improvement
10	Assembly rear door channels found with twist.	Operation sequence changed. Twist correction done after piercing operation.	#191	Routines	Process improvement
11	Welding spots in assembly panel D pillar. Diagnosis: Improper match of weld electrodes.	Operators given tip dressing training for electrode matching. Operator skill record keeping started.	#62	Operator	Process improvement
12	Capping length variation observed in rubber hose. Diagnosis: Hose and screw variation.	Three categories of hoses and matching screws identified. Operators trained to match hoses with screws in assembly.	#218	Operator	Process improvement
13	Breakage on threading of pin. Diagnosis: Stress relieving of threads by flame softening.	Design drawing modified to induction hardening of working surface of pin, keeping threads soft.	#10	Technology	Design quality
14	Rear wiper nozzle discoloration. Diagnosis: Material not UV stable.	Raw material changed to a UV stable material. Design drawing modified.	#288	Technology	Design quality

forgetting are processes that occur simultaneously within organizations, and that mitigating the effects of organizational forgetting is essential to sustain and enhance quality performance in supply chains.

We find that organizational forgetting affects quality gains: 16% of quality gains from autonomous learning and 13% of quality gains from induced learning depreciate every year. Our data allow us to investigate two additional dimensions. First, we leverage Li and Rajagopalan (1998) to classify the quality improvement initiatives as primarily *quality assurance*, *process improvement*, or *design quality*. We find that quality gains from quality assurance initiatives do not depreciate, whereas those from process improvement initiatives depreciate by more than 14% per year. We do not observe significant effects for design quality initiatives. Second, we examine whether organizational forgetting is governed by where the quality knowledge is embedded within vendor organizations. In our setting, quality improvement initiatives had three foci: *technology*, *routines*, and organizational *members*. Consistent with the literature, which finds that individuals are a precarious resource to retain organizational knowledge (Narayanan et al. 2009, David and Brachet 2011, Argote 2013), we find that depreciation of organizational knowledge is highest when it is embedded in specific individuals (26%). Depreciation of knowledge embedded in routines (14%) or in technology (8.86%) is significantly lower. Our study recognizes that remedies chosen to address quality problems depend on the specific manufacturing setting, and our analysis indicates that the impact of organizational forgetting on quality performance is governed by factors along these two dimensions (types of initiatives and place where knowledge is embedded).

This study makes several contributions to the literature. We examine explicitly how organizational forgetting affects vendor quality. We find that the deterioration of quality gains obtained through organizational learning is less than what has been largely observed in the literature for costs and productivity. By studying the impact of organizational forgetting on induced learning, we add to the organizational forgetting literature that has mainly examined the impact of organizational forgetting on autonomous learning. By examining the impact of organizational forgetting on different types of quality improvement initiatives, we provide additional empirical evidence to the quality management literature. By investigating whether organizational forgetting affects quality knowledge embedded in technology, routines, and organizational members, we augment the organizational forgetting literature.

In §2, we develop our hypotheses. In §3, we describe the data and the measures used in our analysis. In §4, we discuss our methodology; we present our results in §5. In §6, we discuss the implications of our findings and the limitations of our work, and suggest directions for future research.

2. Hypotheses

Our hypotheses draw on the organizational learning and organizational forgetting literatures. Although the development and the depreciation of organizational knowledge is often intertwined within organizations, to facilitate exposition, we first consider how organizational knowledge gets built before we examine how organizational knowledge can depreciate.

2.1. Development of Quality Knowledge

Organizational learning refers to the concept that as organizations gain experience they become better at performing tasks. Wright (1936) was the first to document organizational learning when he observed that unit costs in air-frame production declined with cumulative output. Similar observations have been made across a wide cross section of industries, including shipbuilding (Argote et al. 1990), electronics (Adler and Clark 1991), fast food franchises (Darr et al. 1995), and professional services (Boone et al. 2008). Levy (1965) first suggested the idea that organizational learning can be achieved not only by performing tasks repeatedly (autonomous learning) but also by conscious efforts (induced learning), and Dutton and Thomas (1984) developed this idea further. This literature highlights that three broad factors contribute to increased productivity and lowered costs: increased proficiencies of organizational members, improvements in organizational structure and routines, and improvements in organizational technology (Argote 2013). Similarly, quality improvements have also been linked to organizational learning (e.g., Fine 1986, Dada and Marcellus 1994). Li and Rajagopalan (1998) use a theoretical model to show that quality levels improve with cumulative production experience (autonomous learning) and cumulative investment in quality improvement efforts (induced learning). Several empirical studies have supported the theory by showing that both autonomous and induced learning improve quality performance in a variety of settings: continuous manufacturing (Lapré et al. 2000), discrete manufacturing (Ittner et al. 2001), and healthcare (Nembhard and Tucker 2011).

2.2. Depreciation of Quality Knowledge

Though the literature has established the link between organizational learning and organizational quality performance, it has not explicitly examined the impact of organizational forgetting on organizational quality performance. In contrast, several empirical studies find that cost reductions or productivity gains obtained from organizational knowledge developed through production experience depreciate over time (e.g., Darr et al. 1995, Epple et al. 1996, Benkard 2000). The literature suggests three broad reasons for the depreciation of organizational knowledge developed from production experience. First, gains realized through the enhanced proficiency of organizational members may depreciate because of member turnover or transfers (Huber 1991, Narayanan et al. 2009, Argote 2013). Individuals often capture subtle nuances of task performance that are difficult to transfer and may get lost when new individuals perform the tasks. Indeed, such knowledge can depreciate even in the absence of turnover (Weldon and Bellinger 1997, David and Brachet 2011). Second, knowledge obtained from improvements in structures and routines may depreciate because of modifications to processes or amendments to routines (Argote and Epple 1990, Cohen and Bacdayan 1994, Argote 2013). Third, gains from improvements in technology may depreciate because of changes to the products, changes in the underlying technology, or wear and tear of equipment (Argote and Epple 1990, Argote 2013). These reasons are also relevant in the quality domain; hence we expect quality gains obtained from production experience to depreciate over time.

The depreciation of organizational knowledge gained from induced learning has remained relatively unexplored in the literature. It seems likely that the findings related to the depreciation of organizational knowledge gained from autonomous learning would apply as well to the depreciation of organizational knowledge gained from induced learning. But one could also postulate that organizational knowledge developed from induced learning is likely to be better retained within organizations, because induced learning involves deliberate efforts or resources that are not available in the current operations. Moreover, induced learning facilitates a deeper understanding of cause-effect relationships; quality-related knowledge might be better retained within organizations when it encompasses both the "know-how" and "know-why" (Lapré et al. 2000). Consequently, in the absence of clear guidance from the literature on how organizational forgetting will impact organizational-knowledge developed from induced learning, we examine whether the retention of such knowledge is affected by where it is incorporated within vendor organizations. Typically, knowledge developed from quality improvement initiatives is elaborate and gets built into processes, routines, or equipment. However, the dynamic nature of production environments means that processes and routines will undergo changes, and production equipment will suffer from wear and tear (e.g., Epple et al. 1996, Benkard 2000). These factors are likely to depreciate the gains obtained from induced learning. Moreover, our setting involves extensive outsourcing; AMC was outsourcing to 295 vendors spread across many industries. Although firms find it challenging to mitigate the depreciation of organizational knowledge within their operations (Epple et al. 1996, Benkard 2000, Argote 2013), mitigating the depreciation of knowledge at vendors could be even more challenging because it will involve working across organizational boundaries and identifying problems and solutions at vendor facilities. These considerations lead to Hypotheses 1A and 1B.

Hypothesis 1A. *Depreciation of organizational knowledge developed from a vendor's production experience (autonomous learning) will over time reduce the vendor's quality performance.*

Hypothesis 1B. *Depreciation of organizational knowledge developed from targeted quality improvement initiatives (induced learning) at a vendor will over time reduce the vendor's quality performance.*

Hypotheses 1A and 1B are consistent with the literature on how organizational forgetting affects cost reductions and productivity improvements achieved through autonomous learning. In the next two hypotheses, we extend the organizational forgetting literature by investigating certain contingencies that govern how quality gains obtained from induced learning can depreciate.

Li and Rajagopalan (1998) point out that quality performance improves as a result of efforts in quality assurance, process improvement, and design quality. The classification enables us to recognize that the different types of quality improvement efforts use differing mechanisms to address quality issues and require dissimilar investments in resources. This is because quality assurance efforts often require ongoing additional resources in production operations to identify and remove defective products; process improvement efforts typically entail one-time modifications to production processes to avoid the manufacture of defective products; and design quality efforts usually involve investments in product design to make parts easier to manufacture or to obviate the need for inspection. Additionally, the type of quality improvement effort chosen to address a quality problem depends on the specific manufacturing setting (e.g., blow holes in casting can be better handled through improved sand preparation—process improvement—than by using X-rays to test each casting—quality assurance). Given that the different types of quality improvement efforts have differing impact on quality performance, we conjecture that the impact of organizational forgetting could also differ depending on the problem and the manufacturing setting. In what follows, we explore this idea further.

We leverage the literature on knowledge retention within organizations, which suggests that knowledge is assimilated and retained within organizations when it can be incorporated into processes (Argote and Miron-Spektor 2011), codified (Zander and Kogut 1995), or embedded in technology (Epple et al. 1996). Our setting involves quality assurance initiatives that are incorporated into processes (e.g., check hole position using inspection pin, as in Example 2 in Table 1), codified (e.g., a sampling plan, as in Example 4 in Table 1), and embedded in technology (e.g., inspection gauges, as in Example 3 in Table 1). Therefore, the literature predicts that gains from quality assurance initiatives should be relatively well retained at vendors.

In our setting, process improvement initiatives also exhibit features similar to quality assurance initiatives that facilitate the retention of quality gains. For instance, the improvements are incorporated into processes (e.g., change of balancing sequence, as in Example 9 in Table 1) and embedded in technology (e.g., poka-yoke, as in Example 6 in Table 1). However, two factors differentiate how organizational forgetting may affect quality gains from process improvement initiatives compared to gains from quality assurance initiatives. First, process improvement initiatives are usually deployed in machining, assembly, and handling operations pertaining to regular production. The wear and tear in regular production associated with the equipment necessary for these tasks could depreciate some of the quality gains obtained from process improvement efforts. For instance, in Example 8 in Table 1, the sealant applicator in the automated rotary fixture will wear out over time in regular production because it is made of softer material than the solenoid; consequently, it needs to be replaced periodically to ensure proper sealant application. In contrast, quality assurance initiatives involve such changes as measurement of dimensions, inspection plans, and use of inspection gauges that are less subject to wear and tear than production machinery. Second, process improvement initiatives can involve elements of knowledge that are not clearly articulated and are therefore more susceptible to depreciation (Argote 2013). For instance, in Example 7 in Table 1—to ensure correct chamfering of gears—operators must fully butt the components against the cup locator before clamping them for chamfering. In contrast, quality assurance initiatives often involve clearly laid out procedures. These two factors—wear and tear from regular operations and depreciation of knowledge that has not been clearly articulated—can erode quality gains from process improvement initiatives.

The literature finds mixed evidence on whether learning effects are observed for design quality initiatives. Ishikawa (1985, pp. 85–88) reports that a design change addressing a symptom may reduce quality problems temporarily, but points out that only changes that address the fundamental causes can truly resolve quality issues. Adler and Clark (1991) find that engineering changes undertaken to improve product conformance can have a disruptive effect on learning, whereas changes undertaken to improve production can facilitate learning. Similarly, Lapré et al. (2000) find that design quality projects with high conceptual but low operational learning disrupt learning, whereas projects with high conceptual and high operational learning enhance learning. Thus, we expect that quality gains arising from design quality initiatives that address root causes, seek to improve production, or have high conceptual and operational learning will be well retained at vendors because they incorporate the know-how and know-why required to address quality issues (Lapré et al. 2000). However, design quality initiatives that address symptoms, improve product conformance, and have high conceptual but low operational learning may initially improve quality; the quality gains from such efforts will be poorly retained because the root causes are not addressed or due to the disruptive effects on learning. A priori we do not expect all design quality initiatives undertaken at vendors to completely address root causes, seek to improve production, or have high conceptual and operational learning; therefore, we expect some of the quality gains from these initiatives to depreciate over time.

Based on the above discussion, we expect that quality gains from quality assurance initiatives will be better retained at vendors than quality gains from initiatives focused on improving process and design; these considerations lead us to Hypothesis 2.

Hypothesis 2. *Quality gains from cumulative quality assurance initiatives will depreciate less over time than quality gains from cumulative process improvement or design quality initiatives.*

In production environments, organizational knowledge related to quality can be embedded in three potential reservoirs: technology, routines, and organizational members. The choice of where knowledge gets embedded is often determined by the specific organizational and problem setting. To illustrate this, we refer to Example 10 of Table 1, where the quality problem in rear door channel assembly could have been addressed in either of two ways: (i) by changing the sequence of manufacturing operations, which would mean that the quality knowledge gets embedded in organizational routines, or (ii) by investing in advanced piercing equipment, which would mean that quality knowledge gets embedded in technology. AMC and the vendor chose to solve the problem by changing the sequence of operations because investing in the advanced piercing equipment was considered expensive. Such choices could have a bearing on the retention of quality knowledge within vendor organizations. In what follows, we explore this further.

Organizational knowledge can be explicit or tacit. Explicit knowledge is precisely formulated and articulated; tacit knowledge is subconsciously understood or applied and difficult to articulate (Polanyi 1966, Nonaka 1994,Nonaka and von Krogh 2009). Knowledge that is precisely formulated and articulated can be codified because there is an understanding of the underlying mechanisms that link the actions required to perform a task with the performance outcomes produced by the task (Zollo and Winter 2002). Thus, explicit knowledge can be effectively codified.

Technology is an effective repository of codified knowledge, as it allows for knowledge to be embedded in equipment to achieve desired outcomes (Zack 1999, Cross and Baird 2000, Nonaka and von Krogh 2009). Additionally, technology can facilitate the storage, retrieval, and reuse of codified knowledge (Cross and Baird 2000, Argote 2013). Several studies of organizational forgetting observe that knowledge embedded in technology is resistant to depreciation. Argote (2013, p. 105) synthesizes the empirical evidence and states, "... the depreciation rates observed across a variety of settings are consistent with the hypothesis that embedding knowledge in technology is an effective way to mitigate its depreciation." Consequently, we expect that organizational quality knowledge developed from quality improvement initiatives that focus on technology will resist depreciation.

Nelson and Winter (1982) identified routines as repetitive patterns within the schemata of an organization. Organizational routines can serve as an effective means to retain explicit knowledge because they establish stabilized patterns of behavior in response to specific stimuli (Zollo and Winter 2002). However, novelties introduced into processes can affect knowledge retained through routines (Cohen and Bacdayan 1994). Feldman and Pentland (2003) point out that routines have two aspects: the *ostensive* aspect, the repetitive and stable component of routines, which is codifiable; and the *performative* aspect, the varying and flexible component of routines, which is less codifiable and provides room for improvisation by agents. Moreover, they highlight that a routine performed by the same organizational agent repeatedly over time is susceptible to improvisation or adaptation, and this can affect knowledge held within the routine. Zollo and Winter (2002) observe that, in business environments that undergo change, persisting with existing routines can render knowledge obsolete. Thus, some knowledge obtained through quality improvement initiatives that focus on routines can deteriorate over time.

Organizational members acquire and store tacit knowledge. Individuals can capture subtle nuances of task performance that may be difficult to articulate and can acquire task-specific skills through focused training efforts (see Examples 11 and 12 in Table 1). Organizational knowledge embedded in such individuals is likely to depreciate because of turnover and transfers and because individuals may forget even when there is no turnover (Weldon and Bellinger 1997, Narayanan et al. 2009, David and Brachet 2011). Organizational knowledge embedded in routines and in individuals is affected by both turnovers and transfers. However, the impact of member turnover and transfers will be lower for organizational routines than for organizational members, as routines are often documented or incorporated as work instructions, which tend to preserve that knowledge for new members charged with executing the routines. In contrast, subtle nuances of task performance and task-specific skills developed through training are not readily accessible to new members charged with performing the tasks. Additionally, Cohen and Bacdayan (1994) provide evidence that organizational knowledge embedded in organizational members decays faster than knowledge stored in organizational routines. Hypothesis 3 is based on the above considerations.

Hypothesis 3. *Quality gains obtained from quality improvement initiatives that focus on technology will exhibit the least depreciation; quality gains from initiatives that focus on routines will depreciate more; quality gains from initiatives that focus on organizational members will exhibit the most depreciation.*

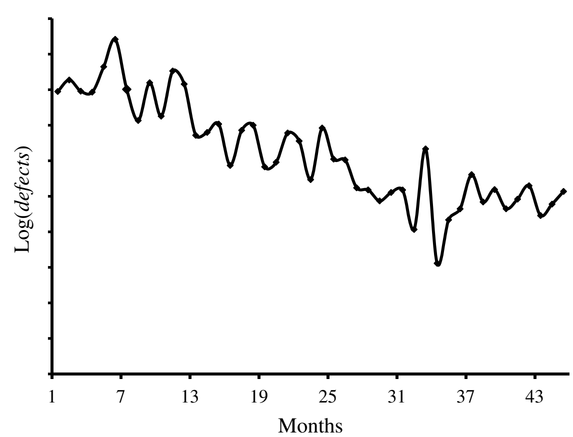
3. Data and Measures

3.1. Data Used for the Analysis

AMC typically provides product design specifications to vendors, which manufacture, inspect, and ship products to AMC's requirements. AMC evaluates the overall quality of vendor products using a comprehensive assessment process that includes incoming inspection, in-process evaluation, and final product testing.

In 2006, AMC created a division called Supplier Improvement Unit (SIU) to improve the quality of components supplied by its vendors. The SIU comprised 20 engineers, drawn from the existing employees of AMC, who worked collaboratively with its 295 vendors. AMC adopted a proactive approach to ensure that vendors would collaborate with the SIU engineers and support the quality improvement efforts. The program was structured so that all the benefits from the quality improvement efforts accrue to the vendors; pricing of vendor components was delinked from the quality improvement program. AMC's quality assessment triggers joint problem-solving efforts between SIU engineers and the vendors; these efforts lead to quality improvement initiatives. From 2006 to 2009, 2,732 quality improvement initiatives were implemented at vendor facilities; the average quality of components supplied to AMC improved by nearly 25%, as shown in Figure 2. (Note that the observed overall quality improvement of 25% is the net effect of the quality gains obtained from organizational learning and the quality losses resulting from organizational forgetting.)

Figure 2 **Incoming Quality Performance at AMC**



Notes. Quality performance is the average quality of components supplied by the 295 vendors of AMC. Defects are measured in ppm. From 2006 to 2009, quality performance of vendors improved by nearly 25%. This improvement is the net effect of the quality gains obtained from organizational learning and the depreciation of quality gains from organizational forgetting. To protect AMC's proprietary information, we do not report details of the scale or the intercept of the vertical axis. This is in line with Lapré et al. (2000), who also do not provide such details to protect proprietary information in the context of their study.

Table 2 Descriptive Statistics

	Mean	Standard deviation	Minimum	Maximum
(1) Log(*defects*)[a]				
(2) *Production experience*	1.96	9.49	0	200
(3) *Quality improvement experience*	0.21	0.93	0	26
(4) *Process improvement*	0.15	0.72	0	17
(5) *Quality assurance*	0.04	0.25	0	7
(6) *Design quality*	0.02	0.13	0	2
(7) *Technology solutions*	0.17	0.54	0	22
(8) *Routines solutions*	0.16	0.54	0	13
(9) *Operator solutions*	0.07	0.30	0	8

[a]To protect AMC's proprietary information, we do not report descriptive statistics for defects. This is in line with Lapré et al. (2000), who also do not report defect rates to protect the proprietary information of the organization that provided the data for their study.

We made multiple visits to AMC and its suppliers and spent more than 17 weeks at their facilities. We conducted 43 semistructured interviews with senior managers and engineers of AMC and its suppliers to acquire a deep understanding of the vendor quality improvement efforts.

3.2. Measures Used for the Analysis

The main variables used in our analysis pertain to measures of organizational quality performance and organizational experience. Below, we describe these variables and the additional controls used in our analysis. We provide the descriptive statistics and the correlations for our data in Tables 2 and 3. We defer the details of how we assess the depreciation of organizational knowledge to §4.1.

3.2.1. Dependent Variable—Organizational Quality Performance. *Defect rate*: We measure vendor quality performance using monthly defect rates. Defect rate (Y_{it}) for vendor i in period t is the defective parts per million (ppm) received at AMC. For a given period it is calculated as $\sum_{j=1}^{n} NumberOfDefectiveParts_j / \sum_{j=1}^{n} TotalPartsSupplied_j \times 10^6$, where n represents the number of distinct components supplied by the vendor. AMC used this measure to evaluate quality performance of vendors over the course of our study; it is also consistent with the literature (e.g., Ittner et al. 2001).

3.2.2. Independent Variables for Hypotheses 1A and 1B—Production Experience and Quality Improvement Experience. *Lagged cumulative production experience*: We measure this as $P_{i(t-1)} = \sum_{t=0}^{t-1} p_{it}$, where p_{it} is the number of units (in hundred thousands) supplied by vendor i in period t. This variable aims to capture the effect of autonomous learning. In our regression models (in §4.1), if the coefficient of this variable is negative and significant, we infer that autonomous learning contributes to lower defect rates.

Since our time series begins with the introduction of the quality improvement program, we assume $p_{i0} = 0$. Because we do not observe the complete history of production experience, we use the exponential form of the learning curve in our analysis. As 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." When information on prior experience was unavailable, scholars have used the exponential form of the learning curve to examine quality-related outcomes in many settings, such as waste reduction (Lapré et al. 2000), complaint rates (Lapré and Tsikriktsis 2006), and surgical mortality (KC and Staats 2012). In the exponential form of the learning curve, the rate at which a process improves depends on the gap between current performance and an ideal performance of the process. The main challenge in using the exponential form is to define ideal performance. However, in the quality domain, zero defects is the natural ideal (Lapré et al. 2000).

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 undertaken at vendor i in period t. This variable seeks to capture the

Table 3 Correlations

	Correlations (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Log(*defects*)	1.00								
(2) *Lagged cumulative production experience*	**−0.20**	1.00							
(3) *Lagged cumulative quality improvement experience*	**−0.21**	**0.18**	1.00						
(4) *Lagged cumulative process improvement*	**−0.20**	**0.18**	—	1.00					
(5) *Lagged cumulative quality assurance*	**−0.18**	**0.17**	—	**0.65**	1.00				
(6) *Lagged cumulative design quality*	**−0.07**	0.01	—	**0.40**	**0.28**	1.00			
(7) *Lagged cumulative technology solutions*	**−0.18**	**0.12**	—	—	—	—	1.00		
(8) *Lagged cumulative routines solutions*	**−0.19**	**0.20**	—	—	—	—	**0.70**	1.00	
(9) *Lagged cumulative operator solutions*	**−0.14**	**0.14**	—	—	—	—	**0.75**	**0.68**	1.00

Notes. Bold denotes significance of less than 5%. We only report correlations for variables used within specific models in our analysis.

effect of induced learning. In our regression models (in §4.1), if the coefficient of this variable is negative and significant, then we infer that induced learning contributes to lower defect rates. Our approach is in line with Lapré et al. (2000) and Nembhard and Tucker (2011), who use similar count-based measures of induced learning.

3.2.3. Independent Variables for Hypothesis 2—Types of Initiatives. We assigned the 2,732 quality improvement initiatives to three categories according to whether they related primarily to (1) quality assurance, (2) process improvement, or (3) design quality. We classified an initiative as "quality assurance" if its principal focus was introduction or modification of vendor inspection procedures (see Examples 1–5 in Table 1). We identified initiatives as "process improvement" if they focused mainly on changes or modifications to vendor production processes (see Examples 6–12 in Table 1). Initiatives were identified as "design quality" if they involved changes or modifications to the design of the components manufactured by vendors (see Examples 13 and 14 in Table 1).

The classification was done by the 20 engineers of the SIU and then validated by AMC's production and quality chiefs independently. The kappa statistic of interrater agreement between these two raters is 0.78, which is high; Landis and Koch (1977) suggest that scores between 0.61 and 0.80 represent substantial agreement. The two chiefs jointly resolved any disagreements in classification. This classification effort identified 458 quality assurance, 2,025 process improvement, and 249 design quality initiatives, and allowed us to decompose our measure for induced learning Q_{it} into three components (S_{it}, R_{it}, D_{it}) to form the independent variables to evaluate Hypothesis 2:

Lagged cumulative quality assurance: This is the number of quality assurance initiatives undertaken at a vendor. It is calculated as $S_{i(t-1)} = \sum_{t=0}^{t-1} s_{it}$, where s_{it} is the number of quality assurance initiatives undertaken at vendor i in period t.

Lagged cumulative process improvement $(R_{i(t-1)})$ and *lagged cumulative design quality* $(D_{i(t-1)})$ are defined analogously.

3.2.4. Independent Variables for Hypothesis 3—Where Quality Knowledge Gets Embedded. To evaluate Hypothesis 3, we classified quality improvement initiatives according to whether they focused primarily on technology, routines, or organizational members. We assigned an initiative to the "technology solutions" category if it addressed quality issues by introducing new equipment, modifications to existing equipment, changes to materials, or changes in design (see Examples 1–3, 6–8, 13, and 14 in Table 1). Initiatives that focused on changes to repetitive patterns of work or introduced new repetitive activity (see Examples 4, 5, 9, and 10 in Table 1) were identified as "routines solutions" (following Nelson and Winter 1982). Initiatives that addressed quality issues primarily by seeking to develop or improve operator skills (via training and monitoring; see Examples 11 and 12 in Table 1) were termed "operator solutions."

Classification began by having AMC's chiefs of vendor development and of quality jointly choose three initiatives that fit each of the three categories: technology solutions, routines solutions, and operator solutions. These nine examples served as a basis on which six SIU engineers undertook classification of the remaining 2,732 initiatives. The two chiefs then validated the resulting classification independently. The kappa statistic of interrater agreement between these two raters is 0.72. Together, the two chiefs resolved any disagreements. The result—1,353 initiatives classified as technology solutions, 1,067 as routines solutions, and 312 as operator solutions—enabled us to decompose our measure for induced learning Q_{it} into three components $(TS_{it}, RS_{it}, OS_{it})$ that form the independent variables to evaluate Hypothesis 3:

Lagged cumulative technology solutions: This is the number of technology solutions initiatives undertaken at a vendor, calculated as $TS_{i(t-1)} = \sum_{t=0}^{t-1} ts_{it}$, where ts_{it} is the number of technology solutions implemented at vendor i in period t.

The variables *lagged cumulative routines solutions* $(RS_{i(t-1)})$ and *lagged cumulative operator solutions* $(OS_{i(t-1)})$ are defined analogously.

3.2.5. Controls. *Vendor fixed effects*: We use vendor-level fixed effects in all our analyses. Given that vendors supply components that belong to one type of technology/industry (such as electrical components, forgings, sheet metal, etc.), vendor fixed effects control for time-invariant factors such as technology and industry types. Additionally, many vendor-specific factors, such as (i) the starting quality performance of vendors when the SIU was created, (ii) the size of the vendor, (iii) the degree of collaboration between the vendors and AMC, (iv) the relative bargaining power between a vendor and AMC, and (v) the geographic distance of the vendor from AMC's facilities (to name a few), can influence quality performance. Vendor fixed effects also control for these vendor-specific time-invariant supply chain related factors. Furthermore, during the course of our study, only one SIU engineer worked with each specific vendor; therefore, the vendor-level fixed effects also control for the specific engineer. Note that the fixed-effects controls in our panel data set allow for arbitrary correlation between the unobserved time-invariant vendor-level characteristics and the observed explanatory variables P_{it} and Q_{it} (Wooldridge 2002, p. 286).

Product mix and model change: From 2006 to 2009, AMC manufactured two to four types of car every month and experienced three model changes. We use indicator variables to control for changes in product mix and model changes. The indicator variable for a model of a particular product takes a value of 1 if the relevant product was produced in a month and 0 otherwise, in line with Thompson (2007).

Time fixed effects: Monthly fixed effects control for factors that change over time, such as technology.

4. Methodology

We examine whether, and to what extent, autonomous and induced learning affect quality performance and then evaluate how organizational forgetting affects quality performance. The analyses were done with STATA (version 13).

4.1. Models to Evaluate Organizational Learning and Organizational Forgetting

In our models, autonomous learning is linked to cumulative production Experience, and induced learning is linked to cumulative quality improvement experience. Following Li and Rajagopalan (1998), we assume that knowledge stock grows with production experience as well as quality improvement experience. We thus represent the knowledge stock K for a vendor by

$$K = \alpha_1 P + \alpha_2 Q, \tag{1}$$

where P and Q represent production and quality improvement experience. We model the defect rate of a vendor $Y(K)$ as a function of the knowledge stock. We assume that the vendors and AMC (through its SIU engineers) work to achieve a target rate for defects (Y^*). Consequently, as Lapré et al. (2000) suggest, the vendors and AMC will exert effort to reduce the performance gap between their current defect rate and the target rate. If μ denotes the learning rate, then the rate of defect reduction can be represented by the differential equation:

$$\frac{dY(K)}{dK} = \mu[Y(K) - Y^*]. \tag{2}$$

In line with the TQM literature (e.g., Deming 1986), we assume that the optimal target rate for defects (Y^*) is zero defects. Indeed, this is the target explicitly set by AMC and its vendors. The solution to differential Equation (2) then becomes

$$Y(K) = \exp(\alpha + \mu K), \tag{3}$$

which links quality performance to the knowledge stock. Note that the learning curve described by (3) is exponential, in line with Levy (1965) and Lapré et al. (2000). Using (1) and (3), we write

$$\ln(Y_{it}) = \alpha_i + \beta_P P_{i(t-1)} + \gamma_Q Q_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}, \tag{4}$$

where Y_{it}, $P_{i(t-1)}$, and $Q_{i(t-1)}$ are as described in §3.2; V_i represents vendor fixed effects, M_t represents product mix and model change controls, C_t represents time fixed effects, and ϵ_{it} represents the error terms. Here, $\beta_P = \mu\alpha_1$ denotes the learning rate for production experience, and $\gamma_Q = \mu\alpha_2$ denotes the learning rate for quality improvement experience. If β_P and γ_Q are negative and significant, then we can infer that both autonomous and induced learning contribute to lower defect rates. We estimate specification (4) using panel data regression. We use clustered standard errors in all our analyses in line with Wooldridge (2002, p. 311) to account for the fact that our data exhibit within-panel serial correlation. (Note: assuming that errors instead arise from an AR(1) process yields similar results.) The results of this analysis are shown in column (L1) of Table 4.

An underlying assumption in the model expressed by Equation (4) is that all knowledge acquired through autonomous and induced learning in the current period is carried over to subsequent periods. We now explicitly change our model to allow for depreciation of organizational knowledge. We use organizational forgetting parameters λ_P and λ_Q to represent the proportion of autonomous and induced knowledge from past periods that is available in future periods. Thus, we denote the stock of autonomous knowledge AK_{it} at time t for vendor i as a function of the stock of autonomous knowledge in the prior period $AK_{i(t-1)}$ and the current production volume p_{it} as $AK_{it} = \lambda_P AK_{i(t-1)} + p_{it}$. We restrict λ_P by $0 \le \lambda_P \le 1$, to ensure that depreciation of knowledge is not greater than the existing stock of knowledge. Similarly, the stock of induced knowledge IK_{it} can be represented as $IK_{it} = \lambda_Q IK_{i(t-1)} + q_{it}$, where $0 \le \lambda_Q \le 1$. We use these parameters to assess the impact of organizational forgetting in the following model:

$$\ln(Y_{it}) = \alpha_i + \beta_P AK_{i(t-1)} + \gamma_Q IK_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}, \tag{5}$$

where the other terms are as described in model (4).

Note that when $\lambda_P = \lambda_Q = 1$, from the definition of $AK_{it} = \lambda_P AK_{i(t-1)} + p_{it}$ we get $AK_{i(t-1)} = \sum_{t=0}^{t-1} p_{it} = P_{i(t-1)}$; similarly, $IK_{i(t-1)} = \sum_{t=0}^{t-1} q_{it} = Q_{i(t-1)}$. Consequently, model (4) is a special case of model (5). If $0 \le \lambda_P, \lambda_Q < 1$, it means that some fraction of knowledge gained from autonomous and induced learning depreciates over time and becomes unavailable.

Table 4 Estimation Results for the Econometric Models to Evaluate Hypotheses 1–3

Dependent variable: Log(*defect rate*)	Main models (1A and 1B)		Impact of different types of initiatives (H2)		Where quality knowledge gets embedded (H3)	
	(L1)	(F1)	(L2)	(F2)	(L3)	(F3)
Hypotheses 1A and 1B						
Lagged cumulative production experience (β_P)	-0.0014^{***}	-0.0017^{***}	-0.0013^{***}	-0.0017^{***}	-0.0014^{***}	-0.0015^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Organizational forgetting for autonomous learning (λ_P)	1	0.9855^{**}	1	0.9866^{**}	1	0.9852^{**}
		(0.005)		(0.005)		(0.004)
Lagged cumulative quality improvement experience (γ_Q)	-0.0316^{***}	-0.0383^{***}				
	(0.006)	(0.007)				
Organizational forgetting for induced learning (λ_Q)	1	0.9883^{**}				
		(0.004)				
Hypothesis 2						
Lagged cumulative quality assurance (γ_S)			-0.0922^{***}	-0.0996^{***}		
			(0.026)	(0.029)		
Organizational forgetting for quality assurance (λ_S)			1	0.9994		
				(0.011)		
Lagged cumulative process improvement (γ_R)			-0.0290^{***}	-0.0351^{***}		
			(0.008)	(0.010)		
Organizational forgetting for process improvement (λ_R)			1	0.9872^{***}		
				(0.003)		
Lagged cumulative design quality (γ_D)			0.1623	0.1535		
			(0.103)	(0.096)		
Organizational forgetting for design quality (λ_D)			1	0.9993		
				(0.028)		
Hypothesis 3						
Lagged cumulative technology solutions (γ_{TS})					-0.0251^{***}	-0.0282^{*}
					(0.009)	(0.013)
Organizational forgetting for technology solutions (λ_{TS})					1	0.9923^{**}
						(0.001)
Lagged cumulative routines solutions (γ_{RS})					-0.0398^{***}	-0.0478^{***}
					(0.017)	(0.015)
Organizational forgetting for routines solutions (λ_{RS})					1	0.9873^{***}
						(0.001)
Lagged cumulative operator solutions (γ_{OS})					-0.0579^{**}	-0.0611^{***}
					(0.027)	(0.019)
Organizational forgetting for operator solutions (λ_{OS})					1	0.9752^{***}
						(0.001)
Constant	6.2082^{***}	6.2271^{***}	6.2548^{***}	6.2664^{***}	6.3517^{***}	6.3478^{***}
	(0.210)	(0.213)	(0.212)	(0.214)	(0.398)	(0.399)
Controls (vendor fixed effects; product mix and model change; time fixed effects)	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.434	0.438	0.437	0.439	0.415	0.416
N	9,224	9,224	9,224	9,224	9,224	9,224

Notes. Values reported are coefficient estimates with standard errors in parentheses. All the organizational learning models (in columns (L1), (L2), and (L3)) and the organizational forgetting models (in columns (F1), (F2), and (F3)) are significant at $p < 0.001$. We recovered all parameter and standard errors in forgetting models (as in columns (F1), (F2), and (F3)) using nonparametric bootstrap techniques. Results use 1,000 replicates with a grid search over organizational forgetting parameters in increments of 0.0001.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Model (5) is not linear in its parameters. The independent variables $AK_{i(t-1)}$ and $IK_{i(t-1)}$ are functions of lagged production volume and lagged quality improvement initiatives and of the organizational forgetting parameters λ_P and λ_Q. Consequently, we cannot use traditional linear regression models, as they will be unable to provide separate estimates of β_P, γ_Q, λ_P, and λ_Q. To address our estimation problem, we use an approach that builds on the nonparametric bootstrap technique proposed by Freedman (1981) and discussed in Davidson and MacKinnon (2006). In brief, this technique involves two simultaneous steps: (i) a two-dimensional grid search over λ_P and λ_Q and (ii) bootstrapping. In the grid search step, we calculate the values of autonomous and induced knowledge stock ($AK_{i(t-1)}, IK_{i(t-1)}$) for each value of λ_P and λ_Q in increments of 0.0001 in the interval $[0, 1]$. Thus, we have 10,000 potential vectors of autonomous and induced knowledge, though at this stage we do not know the optimal values of λ_P and λ_Q. In the bootstrapping step, for given values of λ_P and λ_Q, we draw, with replacement data on the dependent variable, the associated values of autonomous and induced knowledge and the relevant controls to create a simulated sample of our data set. We estimate the regression parameters and the R^2 using the simulated data set. We repeat this process for all potential values of λ_P and λ_Q and store the parameter estimates of α_i, β_P, γ_Q, η_i, ϕ_i, and ψ_i and the corresponding values of λ_P and λ_Q for the model with the highest R^2 as the relevant estimates for this bootstrapping step. We replicate this step 1,000 times. Then we use the means of the parameter estimates and the standard errors of the estimates over these 1,000 bootstrap replicates as the relevant estimates for the model expressed by Equation (5). These results are shown in column (F1) in Table 4. (Additional details of our approach are included in Online Appendix A, which is available as supplemental material at http://dx.doi.org/10.1287/msom.2015.0522.) Our method builds on the approach used in the organizational forgetting literature by Boone et al. (2008), who obtain estimates of organizational forgetting with standard errors for autonomous learning; we extend their approach to obtain estimates of organizational forgetting with standard errors for autonomous as well as induced learning.

A potential concern in the above bootstrapping approach is that correlations in the sample among observations close to each other in time from different vendors could bias results. Consequently, we follow Efron and Tibshirani (1994) and Bertrand et al. (2004), who suggest block bootstrapping for dependent data to preserve the panel structure of the data (and to avoid the creation of simulated samples by random selection of observations from pooled data).

4.2. Models to Evaluate the Impact for Different Types of Quality Improvement Initiatives

To examine how the different types of quality improvement initiatives affect quality performance, we use the variables for lagged cumulative quality assurance ($S_{i(t-1)}$), lagged cumulative process improvements ($R_{i(t-1)}$), and lagged cumulative design quality ($D_{i(t-1)}$) to obtain the following model:

$$\ln(Y_{it}) = \alpha_i + \beta_P P_{i(t-1)} + \gamma_S S_{i(t-1)} + \gamma_R R_{i(t-1)} + \gamma_D D_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}. \quad (6)$$

Next, we define parameters λ_S, λ_R, and λ_D to represent the proportion of induced knowledge related to cumulative quality assurance, cumulative process improvements, and cumulative design quality from past periods that is available in future periods. Let KS_{it}, KR_{it}, and KD_{it} represent the stock of induced knowledge related to quality assurance, process improvements, and design quality, respectively, available for vendor i at time t. The stock of induced knowledge related to quality assurance KS_{it} can then be represented as $KS_{it} = \lambda_S KS_{i(t-1)} + s_{it}$, where s_{it} captures the quality assurance initiatives done in the current period and $0 \le \lambda_S \le 1$. KR_{it} and KD_{it} are represented analogously. We incorporate these parameters to capture the impact of organizational forgetting in the following model:

$$\ln(Y_{it}) = \alpha_i + \beta_P AK_{i(t-1)} + \gamma_S KS_{i(t-1)} + \gamma_R KR_{i(t-1)} + \gamma_D KD_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}. \quad (7)$$

Note that when $\lambda_S = \lambda_R = \lambda_D = \lambda_P = 1$, model (6) is a special case of model (7). If $0 \le \lambda_S, \lambda_R, \lambda_D < 1$, then some of the knowledge gained from induced learning attributable to quality assurance, process improvements, or design quality depreciates and is not available for use in the current month.

We estimate model (6) using panel data regression. These results are shown in column (L2) of Table 4. To estimate model (7), our approach is similar to the one used for model (5). We recovered all the organizational forgetting parameters and standard errors for model (7) using nonparametric bootstrap techniques, using 1,000 replicates with a four-dimensional grid search over λ_S, λ_R, λ_D, and λ_P in increments of 0.0001. These results are shown in column (F2) of Table 4.

4.3. Models to Evaluate the Impact of Where Quality Knowledge Gets Embedded

To evaluate Hypothesis 3, we use the variables for lagged cumulative technology solutions ($TS_{i(t-1)}$), lagged cumulative routines solutions ($RS_{i(t-1)}$), and lagged cumulative operator solutions ($OS_{i(t-1)}$) in the following specification:

$$\ln(Y_{it}) = \alpha_i + \beta_P P_{i(t-1)} + \gamma_{TS} TS_{i(t-1)} + \gamma_{RS} RS_{i(t-1)} + \gamma_{OS} OS_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}. \quad (8)$$

We define λ_{TS}, λ_{RS}, and λ_{OS} to represent the proportion of induced knowledge related to cumulative technology solutions, cumulative routines solutions, and cumulative operators solutions from past periods that is available in future periods. Then we define KTS_{it}, KRS_{it}, and KOS_{it} as the stock of induced knowledge related to quality improvement projects with technology solutions, routines solutions, and operator solutions available with vendor i at time t. This leads to the following specification to capture the impact of organizational forgetting:

$$\ln(Y_{it}) = \alpha_i + \beta_P P_{i(t-1)} + \gamma_{TS} KTS_{i(t-1)} + \gamma_{RS} KRS_{i(t-1)} + \gamma_{OS} KOS_{i(t-1)} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}. \quad (9)$$

We estimate specification (8) using panel data regression. These results are shown in column (L3) of Table 4. We estimate specification (9) using an approach similar to the one used for the estimation of model (7). These results are shown in column (F3) in Table 4.

5. Results

In this section, we present our results and discuss the various tests we did to validate their robustness.

5.1. Results

We observe that the coefficients of lagged cumulative production experience and lagged cumulative quality improvement experience are negative and significant at $p < 0.001$ in columns (L1) and (F1) of Table 4. These results indicate that quality performance improves with cumulative production experience and cumulative quality improvement experience. Thus, in our setting, we confirm that both autonomous and induced learning contribute to enhanced vendor quality performance. This also corresponds to Figure 2, which indicates that the overall defect rates of vendors observed by AMC fell by 25% from 2006 to 2009. Although this represents substantial improvement in quality performance, our subsequent results draw attention to the fact that in the absence of organizational forgetting (i.e., had the gains from organization learning been better retained), AMC could have obtained even better quality performance from its vendors.

In the context of Hypothesis 1A, we refer to column (F1) in Table 4 and find that λ_P is estimated at 0.9855 and is significantly different from 1 at $p < 0.01$. This indicates that organization forgetting exists in autonomous learning and supports Hypothesis 1A. Our results imply that the gains from autonomous learning depreciate by 16.08% every year (annual depreciation is $1 - 0.9855^{12}$ as λ_P represents monthly depreciation rate). To predict the impact of autonomous learning, we follow the approach proposed in Cameron and Trivedi (2009, pp. 103–104) for log-linear models of the general form $\ln(\mathbf{y}) = \mathbf{x}'\boldsymbol{\beta} + \boldsymbol{\epsilon}$, where $\mathbf{E}(y_i/\mathbf{x}_i) = \exp(\mathbf{x}_i'\boldsymbol{\beta})\mathbf{E}[\exp(\epsilon_i)]$. Consequently, as the average annual production for a vendor is 23.52 (1.96×12 months), we estimate that autonomous learning could be expected to reduce defect rates by 3.17% annually (calculated as $(\hat{y}_{P_{i(t-1)}=23.52} - \hat{y}_{P_{i(t-1)}=0})/\hat{y}_{P_{i(t-1)}=0} = -0.0317$). However, the observed reduction in defect rates is 2.66% annually (calculated as $(1 - 0.1608) \times 3.17$), suggesting that organizational forgetting occurred concurrently with autonomous learning.

To evaluate Hypothesis 1B, we refer to column (F1) in Table 4 and find that λ_Q is estimated at 0.9883 and is significantly different from 1 at $p < 0.01$. This indicates that organizational forgetting exists in induced learning and supports Hypothesis 1B. Our results imply that the gains from induced learning depreciate by 13.17% per year. On average, 2.52 (calculated as 0.21×12) quality improvement initiatives are implemented per year at each vendor; so we estimate induced learning should reduce defect rates by 7.65% annually (calculated as $(\hat{y}_{Q_{i(t-1)}=2.52} - \hat{y}_{Q_{i(t-1)}=0})/\hat{y}_{Q_{i(t-1)}=0} = -0.0765$). However, the observed reduction in defect rates is 6.64% annually (calculated as $(1 - 0.1317) \times 7.65\%$), again suggesting that organizational forgetting took place concurrently with induced learning and reduced its effectiveness.

Our conclusion that organizational forgetting affects quality gains obtained from both autonomous and induced learning is consistent with prior studies (on costs and productivity) that report the depreciation of organizational knowledge developed from autonomous learning. An important aspect of our result is that the quality gains obtained from organizational learning are substantial even after accounting for the impact of organizational forgetting. We observed that induced learning at AMC provided nearly 2.5 times larger annual net defect reduction than autonomous learning. AMC and its vendors significantly benefitted from their deliberate, targeted, efforts to improve quality performance.

To examine Hypothesis 2, we refer to column (L2) of Table 4 to verify the presence of organizational learning for the three types of quality improvement initiatives. We find that the estimates of organizational learning are significant only for quality assurance and process improvement initiatives. We now refer to column (F2) and observe that the estimate of organizational forgetting in quality assurance λ_S is not significantly different from 1. This suggests that improvement in quality performance driven by quality assurance initiatives does not depreciate over time. However, λ_R is estimated at 0.9872 and is significantly different from 1 at $p < 0.001$, which suggests that organizational forgetting exists in induced learning for process improvement initiatives. Furthermore, this result indicates that the gains obtained from doing process improvement projects depreciate by 14.32% every year. Additionally, a Wald test indicates that the estimates of λ_S and λ_R are significantly different from each other at $p < 0.01$. We do not make inferences about organizational forgetting for design quality, as the relevant organizational learning estimates are not significant. Thus, our results suggest that the depreciation in knowledge stock for induced learning is mainly caused by depreciation in knowledge related to process improvement.

For Hypothesis 3, we refer to column (L3) in Table 4 to confirm organizational learning for *lagged cumulative technology solutions*, *lagged cumulative routines solutions*, and *lagged cumulative operator solutions*. From column (F3) of Table 4, we observe that the estimates of organizational forgetting for lagged cumulative technology solutions (λ_{TS} at 0.9923), for lagged cumulative routines (λ_{RS} at 0.9873), and for lagged cumulative operators (λ_{OS} at 0.9752), are all significantly different from 1 at $p < 0.01$. Additionally, Wald tests indicate that these organizational forgetting estimates are significantly different from each other at $p < 0.01$. Quality gains obtained from quality improvement initiatives that mainly involve technology exhibit the lowest depreciation: 8.86% of such gains depreciate annually. In contrast, quality gains obtained from quality improvement initiatives that focus on routines and operators depreciate by 14.22% and 26.02%, respectively, per year. Overall, these results support Hypothesis 3.

5.2. Robustness Checks

We undertook various tests to address potential concerns in our overall analysis and to tackle specific issues in the evaluation of our individual hypotheses.

5.2.1. Tests Related to the Overall Analysis. We measure defect rates in monthly intervals. Random fluctuations in vendor defect rates over monthly intervals could affect our results. To address this concern, we aggregated our data over two-, three-, four-, and five-month intervals and evaluated models (4) and (5). The results with quarterly aggregated data are shown in columns (L4) and (F4) of Table 5. Even with temporal aggregation, our results on organizational forgetting are similar to our findings with monthly data.

We use the cumulative count of quality improvement initiatives to capture the impact of induced learning. This approach gives equal weight to all quality improvement initiatives. However, the implementation costs for the different quality improvement initiatives could influence which initiative is implemented. To address this issue, we obtained AMC's costs for each quality improvement initiative to calculate the cumulative cost of quality improvement initiatives. We used this variable to capture the impact of induced learning in our models (4) and (5). The estimation results for these models are shown in columns (L5) and (F5) of Table 5. These results are essentially similar to those obtained in our main models and thus provide additional support to our findings.

We evaluated our models with an additional control for calendar time, because Levin (2000) and Lapré et al. (2000) suggest that experience can also be a function of elapsed time. These results are shown in columns (L6) and (F6) of Table 5. Our results are robust to the inclusion of the control for calendar time.

We used three tests to investigate the potential endogeneity of the decision to undertake quality improvement initiatives. First, we examined two instruments for the potential endogenous variable: (i) the cumulative quality improvement initiatives undertaken at other vendors handled by the same SIU engineer, and (ii) the cumulative quality improvement initiatives undertaken at other vendors within the same industry. However, Hausman tests done after estimating the instrumental variables models failed to reject the null hypothesis that the cumulative quality improvement initiatives variable is exogenous. Second, we evaluated a regression model with quality improvement initiatives as a dependent variable and lagged defects as an independent variable. Lagged defects were not a significant predictor of quality improvement initiatives. Finally, to break the potential endogenous relationship between cumulative quality improvement initiatives and defect rates, we estimated models (4) and (5) 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 analyses.

We also investigated the potential impact of correlation in observations across vendors (i) by evaluating models with standard errors clustered at industry level and at SIU engineer level, and (ii) by estimating models that include experience gained at other vendors within an industry or handled by the same SIU engineer. These analyses reveal that correlation across vendors is not a concern in our context.

5.2.2. Tests Related to the Individual Hypotheses. In the context of Hypothesis 2, the relatively smaller sample of design quality initiatives could explain the absence of significant findings. We used two tests to address this issue. First, we restricted our sample to vendors that implemented at least one design quality initiative. This reduced sample included information on 94 vendors; design quality initiatives accounted for 17% of their quality improvement initiatives. We redid our analysis for this restricted sample; our results for design quality initiatives remain essentially the same. Second, we evaluated our learning models with selective oversampling of design quality initiatives to deal with the unbalanced data, in line with the bootstrapping approach suggested by Estabrooks et al. (2004) and Japkowicz and Stephen (2002). This analysis also

Table 5 Estimation Results with Quarterly Aggregated Data, Experience Measured in Costs, and Controls for Calendar Time

Dependent variable: Log(*defect rate*)

	Quarterly aggregation		Quality improvement projects measured as costs		Calendar time effects	
	(L4)	(F4)	(L5)	(F5)	(L6)	(F6)
Lagged cumulative production experience (β_P)	-0.00089^{***} (0.000)	-0.0009^{***} (0.001)	-0.0013^{***} (0.000)	-0.0017^{***} (0.000)	-0.0014^{***} (0.000)	-0.0017^{***} (0.000)
Organizational forgetting for autonomous learning (λ_P)	1	0.9847^{**} (0.006)	1	0.9861^{**} (0.004)	1	0.9854^{***} (0.001)
Lagged cumulative quality improvement experience (γ_Q)	-0.041^{*} (0.012)	-0.047^{*} (0.015)	-0.0042^{***} (0.001)	-0.0048^{***} (0.001)	-0.0319^{***} (0.006)	-0.0385^{***} (0.008)
Organizational forgetting for induced learning (λ_Q)	1	0.9908^{***} (0.002)	1	0.9914^{**} (0.003)	1	0.9883^{***} (0.003)
Constant	6.8995^{***} (1.127)	6.7851^{***} (0.229)	5.7421^{***} (0.270)	5.7097^{***} (0.269)	6.8315^{***} (0.415)	6.8712^{***} (0.433)
Controls						
Vendor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Product mix	Yes	Yes	Yes	Yes	Yes	Yes
Calendar time	No	No	No	No	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.480	0.489	0.434	0.437	0.435	0.439
N	3,074	3,074	9,224	9,224	9,224	9,224

Notes. Values reported are coefficient estimates with standard errors in parentheses. All the organizational learning models (in columns (L4), (L5), and (L6)) and the organizational forgetting models (in columns (F4), (F5), and (F6)) are significant at $p < 0.001$. We recovered all parameter and standard errors in models (as in columns (F4), (F5), and (F6)) using nonparametric bootstrap techniques. Results use 1,000 replicates with a grid search over organizational forgetting parameters in increments of 0.0001.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

detects no learning effects for design quality initiatives. Additionally, we examined whether design quality initiatives affect quality performance after a lag. Evaluation of our models with the experience variables lagged from two to nine months confirms, once again, the absence of significant findings for design quality initiatives.

In the evaluation of Hypothesis 3, design quality initiatives are encompassed within technology-based improvement initiatives. It is possible that the absence of organizational learning for design quality initiatives may bias the estimates of organizational forgetting for technology-focused initiatives. To address this concern, we excluded design quality initiatives from our data and evaluated models (8) and (9) for the restricted data. Our results remain essentially similar.

We also examined whether endogeneity is a concern in our evaluation of Hypotheses 2 and 3. The approach we used is similar to the one we used for Hypotheses 1A and 1B. For instance, to examine endogeneity of the decision to undertake quality assurance initiatives in the context of Hypothesis 2, we explored two instruments for the potential endogenous independent variable (cumulative quality assurance initiatives): (i) the cumulative quality assurance initiatives undertaken at other vendors handled by the same SIU engineer and (ii) the cumulative quality assurance initiatives undertaken at other vendors within the same industry. However, Hausman tests failed to reject the null hypothesis that the cumulative quality assurance initiatives variable is exogenous. In other words, the independent variable—*cumulative quality assurance initiatives*—is not determined by the dependent variable—log(*defect rate*). We used similar approaches to examine the endogeneity of the decisions to (i) undertake process improvement and design quality initiatives in the context of Hypothesis 2 and(ii) undertake quality improvement initiatives that focus on technology, routines, or organizational members in the context of Hypothesis 3. These additional tests indicate that endogeneity is not a concern in the evaluation of Hypotheses 2 and 3.

6. Discussion and Conclusion

Our study categorizes types of organizational forgetting and their effects on quality performance. Our results confirm that quality competence gained through production experience is degraded over time by organizational forgetting, as has previously been shown to occur in the productivity and cost reduction domains. Additionally, we provide empirical evidence that induced learning is subject to organizational forgetting. In our setting, we find that

16.08% of quality gains from autonomous learning and 13.17% of quality gains from induced learning depreciate annually.

AMC structured its quality improvement program to ensure cooperative relations with its vendors. Moreover, AMC and its vendors worked actively across organizational boundaries to identify causes for quality issues and to develop solutions to address quality problems. This favorable environment led to significant improvement in vendor quality performance; however, organizational forgetting was present even in these favorable circumstances. This supports the conjectures of several scholars that organizational forgetting affects quality performance. This is an area of theory that has not been fully explored. Incorporating the likelihood that organizational learning and organizational forgetting occur concurrently can enrich theoretical models that link learning and quality.

Our results suggest that the impact of organizational forgetting on quality differs from what has been largely observed in many studies that examine the depreciation of organizational knowledge related to costs and productivity. Annual depreciation of quality gains in our study ranges from 13.17% to 16.08%. Prior studies have reported high rates of annual depreciation of production experience, ranging from 39% in aircraft production (Benkard 2000) to more than 90% in automotive assembly (Epple et al. 1996) and shipbuilding (Argote et al. 1990), though Thompson (2007) records negligible depreciation in shipbuilding. We offer two possible explanations for the low rates of depreciation observed in our setting. The first is that quality performance, by its very nature, is often better documented and tracked from the outset of production than are measures of productivity and cost. AMC and its vendors, for example, documented quality extensively. Improvement initiatives are developed after quality problems are observed (e.g., vibration in assembly shroud fan and motor, as in Example 9 in Table 1); the initiatives explore potential causes (e.g., solenoid failure caused by water ingress, as in Example 8 in Table 1); and they seek to identify possible solutions (e.g., arresting rotary movement of inspection gauge, as in Example 1 in Table 1). The deliberate process of addressing quality issues probably facilitates higher retention of knowledge. The second explanation for the relatively slow loss of quality knowledge observed could be the negligible turnover of AMC's SIU engineers during the period studied.

Our project extends the study of organizational forgetting to different types of quality improvement initiatives. In our setting, knowledge depreciation does not happen in all types of improvement efforts. Learning from quality assurance initiatives does not decay over time, whereas learning from process improvement initiatives does decay. Indeed, almost all the depreciation of knowledge reported in this study happens in the knowledge stock related to process improvement initiatives. Discussions with AMC engineers and vendors indicate that the explicit checks associated with quality assurance initiatives are highly effective and subject to minimal forgetting. Additionally, they point out that many changes from quality assurance initiatives are embedded in test equipment, which makes the resulting quality gains robust to depreciation. Process improvement initiatives may be comparatively less robust because they may fail to address all potential causes of the quality problems. For instance, the eighth quality improvement initiative in Table 1 involved improving evenness of application of a sealant. Though sealant application was automated, AMC engineers pointed out that foreign materials in the sealant might cause uneven bonding, leading to the quality issues.

Drawing inferences from these results requires caution. Our results do not suggest that when critical quality issues arise, firms should turn to quality assurance rather than process improvement or design quality initiatives. The choice of the initiative to be pursued depends on the specific solution and problem setting. Indeed, in many instances, process improvement or design quality initiatives may be far more suitable for addressing quality issues than quality assurance initiatives (for instance, in Example 7 of Table 1, hard shifting of gears was better addressed through modifications to the process than by checking the dimensions of each gear prior to assembly). Additionally, firms will need to consider the ongoing cost implications of adding additional quality assurance steps in their production processes. Our findings do suggest, however, that when firms employ process improvement initiatives to address critical quality issues, they must revisit them after a period of time to ensure that quality performance is sustained.

It is intriguing that design quality initiatives are not found to affect overall quality in our setting. Discussions with AMC managers indicate that design quality initiatives are invariably undertaken only when all other options have been exhausted and when the underlying causes are not well understood. Consequently, these projects may not have the relevant understanding of the root causes and, in line with Lapré et al. (2000) and Ishikawa (1985), may not lead to improvement in quality performance.

Our study also responds to the call of Argote (2013) for research to examine the effectiveness of technology in retaining organizational knowledge. We find that quality improvement initiatives that are embedded in technology exhibit lower rates of depreciation (8.86%) than quality improvement initiatives embedded in routines (14.22%) or embedded in organizational members (26.02%). Thus, we validate the underlying assumption in the literature that embedding knowledge in technology is effective in mitigating organizational forgetting. However, our discussions with AMC managers indicate that it is not always possible to address quality issues using technology-focused initiatives because they may be expensive (e.g., investing in advanced piercing equipment to solve the quality problem in rear door channel assemble was considered expensive in Example 10 of Table 1), or because technological solutions may not be feasible (e.g., AMC and the vendor could not identify a technological solution to properly match weld electrodes in Example 11 of Table 1). As a result, changes to routines or improvement of operator skills could be essential to address certain quality issues. Consequently, our results suggest that irrespective of where quality knowledge gets embedded in organizations, firms will need to assess quality improvement solutions regularly to sustain quality performance.

This study classified quality improvement initiatives into different types and identified where quality knowledge was embedded. Such analysis can be done ex ante and hence has practical implications for firms. Our findings are also relevant for managers concerned with quality improvement and can guide them to more informed decision making.

Future research could address some of the limitations of our study. First, we did not consider the costs incurred by vendors to implement the quality improvement initiatives. Vendors were reluctant to share cost information. Even when they did, we found that they did not track costs at the level of detail required for meaningful analysis. Obtaining detailed cost information might provide additional interesting insights. On the one hand, efforts to improve quality may involve additional costs: quality assurance initiatives often add to ongoing costs, process improvement may require investments in process modifications, and design quality efforts may involve investments in design. On the other hand, efforts to mitigate the depreciation of organizational knowledge, too, may require additional investments. One could envisage a study that investigates the quality-cost trade-offs involved in retaining organizational quality knowledge.

Second, we did not observe the solutions that were not implemented. In some instances, the implementation costs of different solutions for a quality issue could have influenced which solution was implemented. Information on such initiatives can provide insights on the short-term and long-term consequences of quality investment decisions. Third, de Holan and Phillips (2004) identify four different modes of organizational forgetting: dissipation, degradation, purging, and suspension. It will be interesting to investigate whether all the modes of organizational forgetting are relevant in the quality domain. Finally, we note that although field data have enriched our study, there are some inevitable limitations in field settings because one can neither measure all aspects (e.g., full production history) nor control all facets (e.g., quality of vendors in second and third tiers). We hope our work will stimulate further theoretical and empirical work on the role of organizational forgetting in quality improvement.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2015.0522.

Acknowledgments

The authors thank Linda Argote, Charles Corbett, Dennis Epple, Vishal Gaur, Srinagesh Gavirneni, Ujjal Mukherjee, Nicholas Petruzzi, and Bradley Staats for valuable comments. The authors thank Ram Ganeshan and Robert Hicks for sharing the analysis related to their paper. They are grateful for feedback from the participants at seminars given at Carnegie Melon University; Georgetown University; Indian Institute of Management, Lucknow; Pennsylvania State University; and Southern Methodist University, and from the participants at various conference presentations. The authors thank Stephen Graves, the associate editor, and the reviewers for helpful feedback that improved the paper substantially.

A. Agrawal's current affiliation is Mays Business School, Texas A&M University, College Station, Texas 77843.

References

Adler PS, Clark KB (1991) Behind the learning curve: A sketch of the learning process. *Management Sci.* 37(3):267–281.

Argote L (2013) *Organizational Learning: Creating, Retaining and Transferring Knowledge*, 2nd ed. (Springer, New York).

Argote L, Epple D (1990) Learning curves in manufacturing. *Science* 247(4945):920–924.

Argote L, Miron-Spektor E (2011) Organizational learning: From experience to knowledge. *Organ. Sci.* 22(5):1123–1137.

Argote L, Beckman SL, Epple D (1990) The persistence and transfer of learning in industrial settings. *Management Sci.* 36(2): 140–154.

Benkard CL (2000) Learning and forgetting: The dynamics of aircraft production. *Amer. Econom. Rev.* 90(4):1034–1054.

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *Quart. J. Econom.* 119(1):249–275.

Boone T, Ganeshan R, Hicks RL (2008) Learning and knowledge depreciation in professional services. *Management Sci.* 54(7): 1231–1236.

Cameron AC, Trivedi PK (2009) *Microeconometrics Using Stata* (Stata Press, College Station, TX).

Cohen M, Bacdayan P (1994) Organizational routines are stored as procedural memory: Evidence from a laboratory study. *Organ. Sci.* 5(4):554–568.

Cross R, Baird L (2000) Technology is not enough: Improving performance by building organizational memory. *Sloan Management Rev.* 41(3):69–78.

Dada M, Marcellus R (1994) Process control with learning. *Oper. Res.* 42(2):323–336.

Darr ED, Argote L, Epple D (1995) The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises. *Management Sci.* 41(11):1750–1762.

David G, Brachet T (2011) On the determinants of organizational forgetting. *Amer. Econom. J.: Microeconomics* 3(3):100–123.

Davidson R, MacKinnon JG (2006) Bootstrap methods in econometrics. Mills TC, Patterson K, eds. *Palgrave Handbooksof Econometrics: Vol.* 1; *Econometric Theory* (Macmillan, Basingstoke, UK), S2–S18.

de Holan PM, Phillips N (2004) Remembrance of things past? The dynamics of organizational forgetting. *Management Sci.* 50(11): 1603–1613.

Deming WE (1986) *Out of the Crisis* (MIT Press, Boston).

Dutton JM, Thomas A (1984) Treating progress functions as a managerial opportunity. *Acad. Management Rev.* 9(2):235–247.

Efron B, Tibshirani R (1994) *An Introduction to the Bootstrap*, Monograph in Applied Statistics and Probability, Vol. 57 (Chapman and Hall, New York).

Epple D, Argote L, Murphy K (1996) An empirical investigation of the microstructure of knowledge acquisition and transfer through learning by doing. *Oper. Res.* 44(1):77–86.

Estabrooks A, Jo T, Japkowicz N (2004) A multiple resampling method for learning from imbalanced data sets. *Computational Intelligence* 20(1):18–36.

Feldman MS, Pentland BT (2003) Reconceptualizing organizational routines as a source of flexibility and change. *Admin. Sci. Quart.* 48(3):94–118.

Fine CH (1986) Quality improvement and learning in productive systems. *Management Sci.* 32(10):1301–1315.

Freedman DA (1981) Bootstrapping regression models. *Ann. Statist.* 9(6):1218–1228.

Huber GP (1991) Organizational learning: The contributing processes and the literatures. *Organ. Sci.* 2(1):88–115.

Ishikawa K (1985) *What Is Total Quality Control? The Japanese Way* (Prentice-Hall, NJ).

Ittner CD, Nagar V, Rajan MV (2001) An empirical examination of dynamic quality-based learning models. *Management Sci.* 47(4):563–578.

Japkowicz N, Stephen S (2002) The class imbalance problem: A systematic study. *Intelligent Data Anal.* 6(5):429–449.

Johnson & Johnson (2011) Janssen identifies trace amounts of TBA in 5 batches of PREZISTA® (darunavir) in the EU and Canada. (May 11), http://www.investor.jnj.com/releasedetail.cfm?ReleaseID=576210.

KC DS, Staats BR (2012) Accumulating a portfolio of experience: The effect of focal and related experience on surgeon performance. *Manufacturing Service Oper. Management* 14(4): 618–636.

Landis JR, Koch GG (1977) An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics* 33(2):363–374.

Lapré MA, Tsikriktsis N (2006) Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. *Management Sci.* 52(3):352–366.

Lapré MA, Mukherjee AS, Wassenhove LV (2000) Behind the learning curve: Linking learning activities to waste reduction. *Management Sci.* 46(5):597–611.

Lee HL, Tseng MM, Hoyt D (2008) Unsafe for children: Mattel's toy recall supply chain management. Case study, Graduate School of Business, Stanford University, CA.

Levin DZ (2000) Organizational learning and the transfer of knowledge: An investigation of quality improvement. *Organ. Sci.* 11(6):630–647.

Levy FK (1965) Adaptation in the production process. *Management Sci.* 11(6):136–154.

Li G, Rajagopalan S (1998) Process improvement, quality, and learning effects. *Management Sci.* 44(11):1517–1532.

Narayanan S, Balasubramanian S, Swaminathan JM (2009) A matter of balance: Specialization, task variety, and individual learning in a software maintenance environment. *Management Sci.* 55(11):1861–1876.

Nelson RR, Winter SG (1982) *An Evolutionary Theory of Economic Change* (Harvard University Press, Boston).

Nembhard IM, Tucker AL (2011) Deliberate learning to improve performance in dynamic service settings: Evidence from hospital intensive care units. *Organ. Sci.* 22(4):907–922.

Nonaka I (1994) A dynamic theory of organizational knowledge creation. *Organ. Sci.* 5(1):14–37.

Nonaka I, von Krogh G (2009) Perspective: Tacit knowledge and knowledge conversion: Controversy and advancement in organizational knowledge creation theory. *Organ. Sci.* 20(3): 635–652.

Polanyi M (1966) *The Tacit Dimension* (Anchor Day Books, New York).

Singer N, Abelson R (2011) Can Johnson & Johnson get its act together? *New York Times* (January 15), http://www.nytimes.com/2011/01/16/business/16johnson-and-johnson.html?pagewanted=all&_r=0.

Sodhi MS, Tang CS (2012) Application: Mitigating new product development risks—The case of the Boeing 787 Dreamliner. *Managing Supply Chain Risk*, International Series in Operations Research and Management Science (Springer, New York), 161–179.

Thompson P (2007) How much did the liberty shipbuilders forget? *Management Sci.* 53(6):908–918.

Weldon MS, Bellinger KD (1997) Collective memory: Collaborative and individual processes in remembering. *J. Experiment. Psych.-Learn. Memory Cognition* 23(5):1160–1175.

Wooldridge J (2002) *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. (MIT Press, Boston).

Wright TP (1936) Factors affecting the cost of airplanes. *J. Aeronautical Sci.* 3(4):122–128.

Zack MH (1999) Managing codified knowledge. *Sloan Management Rev.* 40(4):45–58.

Zander U, Kogut B (1995) Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organ. Sci.* 6(1):76–92.

Zollo M, Winter SG (2002) Deliberate learning and the evolution of dynamic capabilities. *Organ. Sci.* 13(3):339–351.