Does Organizational Forgetting Affect Vendor Quality Performance? – An Empirical Investigation

Date: April 08, 2014

Anupam Agrawal
Department of Business Administration, University of Illinois at Urbana-Champaign, Champaign, Illinois 61820,
anupam@illinois.edu

Suresh Muthulingam
Smeal College of Business, Pennsylvania State University, University Park, Pennsylvania16802,
suresh@psu.edu

Abstract
While previous studies have examined how the development of organizational knowledge (organizational learning) affects quality performance, we investigate how the depreciation of organizational knowledge (organizational forgetting) affects vendor quality performance. We use data on 2,732 quality improvement initiatives undertaken by a car manufacturer at 295 vendors. We find that organizational forgetting affects quality gains obtained from learning-by-doing (autonomous learning) and from undertaking quality improvement initiatives (induced learning); over 16% of quality gains from autonomous learning and over 13% of the quality gains from induced learning depreciate every year. Depreciation of quality gains mainly occurs through the degradation of assimilated organizational quality knowledge and the impact of organizational forgetting on quality is lower than what has been observed in the literature for costs and productivity. Further, the impact of organizational forgetting i) differs across the types of quality improvement efforts: quality gains from process improvement initiatives depreciate while those from quality assurance initiatives do not, and ii) depends on where quality knowledge gets embedded within vendor organizations: depreciation of quality gains is lower for knowledge embedded in technology than for knowledge embedded in organizational routines or organizational members. We contribute by providing insights on how organizational forgetting affects quality performance.

Keywords: Quality Management, Process Improvement, Quality Assurance, Design Quality, Organizational Learning, Organizational Forgetting, Vendor Management

1. Introduction
Since the advent of the quality movement in the early eighties, firms have strived to ensure quality in their manufacturing operations. The emphasis on quality has continued with the increased outsourcing of manufacturing activities, and many firms focus on ensuring quality in their supply chains. However in the recent past, despite the focus on quality management, many firms have faced quality issues in their supply chains. Some high profile examples include, Johnson and Johnson’s (JNJ) 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). Additionally, the respective firms faced significant financial consequences: JNJ’s 2010 revenues
fell by $290 million and Mattel incurred financial costs of around $110 million. What is intriguing about these examples is that quality problems occurred even though specific measures were undertaken by the firms to avoid such issues. For instance, after the recall in 2010, JNJ undertook a number of actions in its infectious disease business to avoid chemical contamination. However, in 2011, JNJ initiated another recall after it found similar chemical contaminants in the medicines manufactured by vendors for the infectious disease business (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, and yet recalls were initiated due to excessive lead paint in toys manufactured by the same vendors (Sodhi and Tang 2012). These examples suggest that sometimes efforts to improve quality performance of vendors may not be effective. This may be because vendors find it challenging to learn and develop quality knowledge required to address quality issues, or because the quality knowledge developed by vendors depreciates over time. Consequently, to ensure quality performance in supply chains it is essential to study how quality knowledge is built, sustained, or depreciated within supply chains, and these issues form the core of our research. A significant body of work has examined how organizational quality knowledge gets built through organizational learning (e.g., Lapré et al. 2000, Ittner et al. 2001), however not much work has examined whether organizational quality knowledge depreciates. In manufacturing firms a variety of factors, such as product changes, amendments to routines, member turnover or equipment wear and tear, can depreciate organizational knowledge. The literature refers to this depreciation of organizational knowledge as organizational forgetting (Benkard 2000, Argote 2013), and several scholars have suggested that organizational forgetting may affect quality performance (Li and Rajagopalan 1998, Lapré et al. 2000). In line with this literature, we investigate how organizational forgetting affects quality performance and examine potential contingencies that influence the impact of organizational forgetting on quality.

This study uses data from AMC (a large automotive manufacturer in Asia, who requested confidentiality). In 2006, AMC initiated a program to improve the quality of incoming components for its car division. Over the next four years, a team of engineers from AMC worked collaboratively with their vendors to implement 2,732 quality improvement initiatives at vendor facilities. Table 1 provides select examples of quality improvement initiatives implemented at vendors. In this period, we interacted closely with AMC and its vendors, which allowed us to recognize several nuances associated with improving vendor quality performance. To illustrate this, we refer to Figure 1, which shows the quality performance of a sheet metal stamping vendor. We observe that quality performance improves over time, albeit with some variation. In an interview, a manager at the vendor stated, “Initially when we started, we had quality problems, but as our workers became more familiar with producing parts with tighter tolerances for AMC, our quality levels improved.” This quote suggests that quality knowledge gets built as vendors gain experi-
ence. In Figure 1, we also notice periods when quality performance depreciates. An AMC engineer explained, “Sometimes people resign, key personnel go on leave, new apprentices ignore processes, or raw material suppliers change, and the vendor quality may deteriorate!” This quote suggests that vendor quality knowledge may erode over time. The data from the quality improvement program of AMC enables us to examine how organizational learning and organizational forgetting affect vendor quality performance.

The literature has identified two mechanisms of organizational learning that facilitate quality improvement. Firms can improve their quality either by performing the same task repeatedly (this learning from production experience is known as autonomous learning), or by undertaking conscious actions to improve quality (this learning through quality improvement experience is known as induced learning). The underlying assumption in these mechanisms is that quality gains from each unit of production and each quality improvement initiative are retained over time. However, several studies have shown that cost reductions or productivity gains obtained from autonomous learning depreciate over time (e.g., Darr et al. 1995, Benkard 2000). In some manufacturing firms, over 90% of the cost reduction or productivity gains obtained from production experience depreciate within a year (Argote et al. 1990, Epple et al. 1996). While the literature has examined the depreciation of organizational knowledge gained from autonomous learning, the depreciation of organizational knowledge gained from induced learning has remained relatively unexplored. One may assume that the research findings based on cost or productivity measures may also apply to the quality domain; however Levin (2000) provides evidence to the contrary. In the context of product reliability he finds that learning does not depend on production experience but depends on elapsed time. Moreover, Levin (2000) indicates that organizational performance cannot be restricted to a single construct such as cost or productivity and that quality also constitutes an important dimension of organizational performance. Therefore, we investigate how organizational forgetting affects quality performance (measured in terms of defect rates) achieved through autonomous and induced learning.

We find that organizational forgetting has a lower effect on quality than what has been observed in the literature for cost and productivity; however the effect is still significant as 16.08% of quality gains from autonomous learning and 13.17% of quality gains from induced learning depreciate every year. We also delve deeper to investigate how different modes of organizational forgetting affect the retention of organizational quality knowledge. De Holan and Phillips (2004) suggest that organizational knowledge can depreciate unintentionally because of organizational failure to consolidate and assimilate new knowledge (this is called dissipation) or because of organizational inability to maintain acquired knowledge over time (this is called degradation). In our context, degradation mainly contributes to the depreciation of organizational quality knowledge developed from autonomous and induced learning.
We then investigate two potential contingencies that influence how organizational forgetting affects quality. First, we examine how the quality gains obtained from different types of quality improvement initiatives are affected by organizational forgetting. We leverage Li and Rajagopalan (1998) to identify whether the quality improvement initiatives in our data pertain to quality assurance, process improvement, or design quality; and find that gains from quality assurance initiatives do not depreciate, while those from process improvement initiatives depreciate by over 14% every year. Second, we examine whether organizational forgetting is governed by where quality knowledge gets embedded within vendor organizations. In our setting, quality improvement initiatives could develop quality knowledge by focusing on technology, routines, or organizational members. Consistent with the literature which finds that individuals are a precarious resource to retain organizational knowledge (Argote 2013, Narayanan et al. 2009, David and Brachet 2011); we find that depreciation of organizational knowledge is highest when it is embedded in organizational members (26.02%). In contrast, depreciation of organizational knowledge when it is embedded in routines (14.22%) or in technology (8.86%) is significantly lower.

Our paper makes several contributions to the Operations Management (OM) literature. First, we explicitly examine how organizational forgetting affects quality and are one of the first in OM to do so. Second, we are the first to demonstrate the impact of organizational forgetting for induced learning. Additionally, we show that organizational forgetting has a lower impact on quality than what has been observed in the context of costs or productivity. Third, by examining the impact of organizational forgetting on different types of quality improvement initiatives, we extend the findings from the quality management literature. Fourth, by investigating whether organizational forgetting affects quality knowledge embedded in technology, we validate underlying assumptions in the organizational forgetting literature. Our study is also relevant for practice as it provides insights on managing quality in supply chains.

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

2. Hypotheses

To develop our hypotheses, we draw on the learning literature to understand how organizational knowledge gets built and then examine how organizational knowledge can depreciate.

2.1 Development of Quality Knowledge

Organizational learning refers to the concept that as organizations gain experience they develop knowledge which enables them to 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). The idea that organizational learning can be achieved by performing tasks repeatedly (autonomous learning) and by conscious efforts (induced learning) was first suggested by Levy (1965) and developed further by Dutton and Thomas (1984). This literature highlights that as organizations gain experience they learn and develop knowledge which enables them to raise productivity or lower costs because of the following three broad factors: increased proficiencies of organizational members, improvement in organizational structure and routines, and improvements in organizational technology (Argote 2013). Similarly, a link between organizational learning and quality performance has also been established (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). Aligned with this body of work, several empirical studies have shown that both autonomous and induced learning improve quality performance in a variety of settings, such as continuous manufacturing (Lapré et al. 2000), discrete manufacturing (Ittner et al. 2001) and healthcare (Nembhard and Tucker 2011).

### 2.2 Depreciation of Quality Knowledge

An inherent assumption in the models that link organizational learning to quality performance is that gains from organizational knowledge developed with experience do not depreciate over time. However, the literature indicates that organizational knowledge may depreciate because of three broad reasons. 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). This is because individuals often capture subtle nuances of performing tasks which are difficult to transfer and which may get lost when individuals no longer perform the tasks. Moreover, research shows that organizational knowledge embedded in individuals can depreciate even in the absence of turnover (Weldon and Bellinger 1997, David and Brachet 2011). Second, gains obtained from improvements in structures and routines may depreciate because of modifications to processes and amendments to routines (Argote and Epple 1990, Argote 2013). For instance, Cohen and Bacdayan (1994) demonstrate (using experiments) that novelties in processes affect the effectiveness of routines. Third, gains from improvements in technology may depreciate because of changes to the products, changes to the underlying technology, or wear and tear of equipment (Argote and Epple 1990, Argote 2013).

#### 2.2.1 Depreciation of Quality Knowledge Developed from Production Experience
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). In line with this literature which indicates that organizational knowledge can depreciate, we expect that quality gains obtained from organizational knowledge developed through production experience will also depreciate over time.

**2.2.2 Depreciation of Quality Knowledge Developed from Quality Improvement Experience**

To investigate depreciation of quality knowledge developed from quality improvement experience, we draw on Lapré et al. (2000), who point out that quality improvement initiatives must develop knowledge about cause-effect relationships and validate solutions to effectively address quality issues. Typically, knowledge developed through such initiatives is elaborate and is built into processes, routines, or equipment. However, given the dynamic nature of the production environment at vendor facilities, processes and routines are likely to undergo changes and production equipment are likely to deteriorate, which may lead to the depreciation of quality knowledge developed from quality improvement efforts.

Additionally, several studies find significant depreciation of organizational knowledge in manufacturing firms (e.g., Epple et al. 1996, Benkard 2000), which suggests that firms find it challenging to mitigate depreciation of organizational knowledge within their operations. AMC deals with 295 vendors spread across many industries, which will make it more challenging to mitigate depreciation of organizational knowledge at vendor facilities. Therefore, we hypothesize:

**Hypothesis 1a:** Depreciation of organizational knowledge developed from production experience over time will reduce the effect of autonomous learning on vendor quality performance.

**Hypothesis 1b:** Depreciation of organizational knowledge developed from quality improvement experience over time will reduce the effect of induced learning on vendor quality performance.

We refer to de Holan and Phillips (2004) to investigate how different modes of organizational forgetting affect the retention of organizational quality knowledge. They identify four modes of organizational forgetting: 1) dissipation, 2) degradation, 3) purging and 4) suspension. Dissipation and degradation conform to the accidental mode of organizational forgetting where organizations are unable to retain essential knowledge due to faulty or inadequate memory systems. Dissipation occurs when organizations fail to consolidate and assimilate new knowledge in the organizational memory systems. It signifies the state where organizations acquire knowledge to perform tasks but the knowledge is unstable and deteriorates rapidly. Degradation refers to the knowledge depreciation that happens after satisfactory performance has been achieved. It represents the state where organizations acquire knowledge to achieve acceptable performance; however over time they fail to maintain knowledge and organizational performance deteriorates. In contrast, purging and suspension correspond to the purposeful mode of organizational forgetting.
Purging represents situations where organizations ‘unlearn’ old ways of doing things as part of the efforts to learn something new. As a complement to organizational learning, purging is considered desirable as it involves casting aside old methods in a bid to adopt new essential processes (Bettis and Prahalad 1995). Suspension refers to the state when organizations fail to adopt or entertain new innovations or practices.

In our context, as SIU engineers worked collaboratively with vendors to develop solutions to quality issues, vendors are likely to adopt the quality improvement solutions and therefore suspension is not relevant. With the adoption of quality improvement solutions, vendors are likely to develop quality knowledge leading to improved quality performance. This implies that vendors ‘unlearn’ processes that cause quality issues and provides indirect support for the presence of purging. Moreover, as quality improvement initiatives typically have well laid out procedures and are supported with equipment and tools we expect vendors to consolidate the quality knowledge within their organizations. Thus, we do not anticipate quality knowledge to be unstable, and do not expect vendors to lose organizational quality knowledge rapidly, or in other words we do not expect to find evidence for dissipation. Finally, on account of the dynamic production environment at vendor facilities the organizational quality knowledge consolidated through quality improvement initiatives is likely to depreciate over time which indicates the presence of degradation. Based on the above discussion, we hypothesize:

**Hypothesis 2:** Organizational forgetting will manifest in different modes to affect the retention of organizational quality knowledge at vendors: Quality knowledge will depreciate due to degradation and will not be affected by dissipation, while purging will support the development of quality knowledge.

In the next two hypotheses, we investigate potential contingencies that influence how organizational forgetting affects quality performance. First, we examine how organizational forgetting affects quality gains obtained from the different types of quality improvement initiatives. Li and Rajagopalan (1998) point out that quality performance improves as a result of efforts in quality assurance, process improvement and design quality. This is because quality assurance efforts identify and remove defective products, process improvement efforts ensure that defective products are not produced, and design quality efforts make parts easier to manufacture or design products that do not need inspection.

To evaluate the impact of organizational forgetting, we turn to the literature on knowledge retention within organizations. This literature 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). Additionally, quality assurance initiatives involve
clearly laid out procedures (e.g., accept components if they conform to inspection gauges, as in examples 1 and 3 in Table 1) and therefore we expect the gains from quality assurance initiatives to be better retained at vendors.

In our context, process improvement initiatives also exhibit features similar to quality assurance initiatives that facilitate retention of quality gains. For instance, such improvement initiatives can be 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, unlike quality assurance initiatives that involve clearly laid out procedures, process improvement initiatives can involve some 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. Additionally, process improvement initiatives are often integrated into production processes and may be subject to wear and tear involved with regular production. For instance, in example 8 in Table 1, the sealant applicator in the automated rotary fixture is made of softer material than the solenoid and needs to be replaced periodically to ensure proper sealant application. Consequently, quality gains from process improvement initiatives can erode due to the depreciation of knowledge that may not be clearly articulated and due to depreciation from regular operations.

With regard to design quality initiatives, the literature finds mixed evidence. Ishikawa (1985, p 85-88) illustrates that design changes which address a symptom may avoid quality problems temporarily, and points out that only changes that address the fundamental causes can completely resolve quality issues. Adler and Clark (1991) find that engineering changes undertaken to improve product conformance can have a disruptive effect on learning, while 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, while projects with high conceptual and high operational learning enhance learning. Therefore, quality gains from design quality initiatives can depreciate because they do not address the fundamental cause, they disrupt learning, or they have inadequate conceptual and operational learning. Based on the above discussion, we infer that quality gains from quality assurance initiatives will be better retained at vendors while quality gains from process improvement and design quality initiatives may depreciate over time. Therefore, we hypothesize:

**Hypothesis 3:** Quality gains from cumulative quality assurance initiatives will depreciate less over time than quality gains from cumulative process improvement or cumulative design quality initiatives.

We now examine the impact of where the quality knowledge gets embedded within vendor organizations. Towards this end, we refer to the characterization of knowledge as explicit or tacit knowledge. Ex-
Explicit knowledge refers to knowledge that is precisely formulated and articulated, while tacit knowledge represents knowledge that is subconsciously understood or applied and difficult to articulate (Polanyi 1966, Nonaka 1994, Nonaka and van Krogh 2009). Explicit knowledge is amenable to codification. This is because knowledge can be precisely formulated and articulated only if 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). Technology can serve as an effective repository of codified knowledge, as it allows for knowledge to be embedded in equipment to ensure tasks achieve desired outcomes (Zack 1999, Cross and Baird 2000, Nonaka and van Krogh 2009) and as it can serve as a reservoir for storage, retrieval and reuse of knowledge (Cross and Baird 2000, Argote 2013).

Several studies on 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 be resistant to 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). While the literature suggests that routines are effective in maintaining organizational knowledge, it also finds that novelties introduced in 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 provides repetitive and stable component of routines, while the performative aspect of routines provides variation and flexibility in the organization. The performative aspect of routines is less codifiable and provides room for improvisation by agents. Even the same 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. Additionally, in business environments that undergo change, persisting with existing routines can render knowledge obsolete (Zollo and Winter 2002). Thus, some of the quality knowledge obtained from quality improvement initiatives that focus on routines can deteriorate over time.

Organizational members represent effective repositories to acquire and store tacit knowledge within organizations because individuals can capture subtle nuances of performing tasks which may be difficult to articulate. However, organizational knowledge embedded within organizational members 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). Additionally,
organizational knowledge stored in organizational members is expected to decay faster than knowledge stored in organizational routines (Cohen and Bacdayan 1994). Based on the above discussion, we hypothesize:

**Hypothesis 4**: Quality improvement initiatives that focus on technology will exhibit the lowest depreciation of organizational quality knowledge, followed by quality improvement initiatives that focus on routines and quality improvement initiatives that focus on organizational members.

### 3. Data and Measures

#### 3.1 Data Used for the Analysis

In 2006, AMC created a division called ‘Supplier Improvement Unit’ (SIU, from now onwards) to spearhead the efforts to improve the quality of components supplied by their vendors. The SIU comprised 20 engineers, drawn from the existing employees of AMC, who worked collaboratively with its 295 vendors. AMC typically provides product design specifications to vendors, who in turn manufacture the products, inspect and ship them to meet AMC’s requirements. The overall quality of products supplied by vendors is evaluated by AMC using a comprehensive assessment process within AMC’s operations. This includes incoming inspection, in-process evaluation and final product testing. The assessment of vendor quality forms the basis for the quality improvement initiatives that are identified as a result of joint problem-solving efforts between SIU engineers and the vendors. From 2006 to 2009, 2,732 quality improvement initiatives were implemented at vendor facilities and the average quality of components supplied to AMC improved by nearly 25%, as shown in Figure 2. We collected the data on all 2,732 quality improvement initiatives as well as the data on the monthly vendor-level quality for this period. We supplemented the data with multiple visits to AMC and its suppliers. We spent over 17 weeks at AMC and its suppliers and conducted 43 semi-structured interviews with senior managers and engineers of AMC and its suppliers. This facilitated a deep understanding of the quality improvements efforts undertaken at vendor facilities.

#### 3.2 Measures Used for the Analysis

To investigate organizational forgetting, we start by establishing that vendors develop knowledge to address quality issues. To do this, we leverage the literature on organizational learning (e.g. Benkard 2000, Argote 2013) which maintains that knowledge is developed with experience and indicates that when experience affects organizational performance it indicates the presence of learning. Then, we establish that knowledge developed at the vendors depreciates. To do this, we leverage the literature on organizational forgetting (e.g. Epple et al. 1996, Benkard 2000, Boone et al. 2008) which infers that organizational knowledge depreciates when the impact of experience on organizational performance outcomes decays over time. Consequently, the main variables used in our analysis pertain to measures of organizational
quality performance and measures of organizational experience. We describe these variables and the additional controls used in our analysis below, and defer the details of how we assess the depreciation of organizational knowledge to Section 4.1.

3.2.1 Dependent Variable

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

$$\frac{\sum_{j=1}^{n} Number\ of\ Defective\ Parts_{j}}{\sum_{j=1}^{n} Total\ Parts\ Supplied_{j}} \times 10^6,$$

where $n$ represents the number of distinct components supplied by the vendor. Our measure of defect rates is consistent with the approach adopted in the literature (e.g., Ittner et al. 2001). Moreover, AMC has used this measure to evaluate quality performance of vendors over the course of our study.

3.2.2 Independent Variables for Hypotheses 1a and 1b

We use the following lagged measures of experience to evaluate our hypotheses:

Lagged Cumulative Production Experience – To capture the effect of autonomous learning we use production experience measured as $P_i(t-1) = \sum_{t=0}^{t-1} p_{it}$, where $p_{it}$ is the number of units (in 100,000) supplied by vendor $i$ in period $t$. The start of our time series coincides with the introduction of the quality improvement program, and therefore we assume that $p_{i0} = 0$. As we do not observe the complete history of production experience, we use the exponential form of the learning curve in our analysis. This is because, as Lapré and Tsikriktsis (2006) 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.” In the exponential form of the learning curve the rate of improvement for a process depends on the gap between the current performance and the ideal performance of the process. The main challenge in using the exponential form is to determine the ideal performance of the process. However, the quality domain provides a natural target for the aspirational ideal for a process i.e. zero defects (Lapré et al. 2000). Additionally, 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).

Lagged Cumulative Quality Improvement Experience– To capture the effect of induced learning we use quality-improvement experience measured as $Q_i(t-1) = \sum_{t=0}^{t-1} q_{it}$, where $q_{it}$ is the number of quality improvement initiatives done at vendor $i$ in period $t$. This is in line with Lapré et al. (2000) and Nembhard and Tucker (2011), who use similar count based measures to capture the impact of induced learning.
We modify the experience variables used for hypotheses 1a and 1b to identify ‘new’ and ‘old’ components of experience. We define ‘new’ experience as the experience gained in the last ‘h’ months and ‘old’ experience as the cumulative experience gained prior to the last ‘h’ months. (The details of how we identify the appropriate number of months ‘h’ to be considered for recent experience are provided later in Section 4.2.) This allows us to split our measures of production $P_{it}$ and quality-improvement $Q_{it}$ experience to create the variables to evaluate our hypothesis on the different modes of organizational forgetting:

‘New’ Cumulative Production Experience – This represents recent production experience and is measured as

$$P_{i(t-1),new} = \sum_{k=t-h-1}^{t-1} P_{ik}.$$  

‘Old’ Cumulative Production Experience – This represents production experience gained in the past and is measured as

$$P_{i(t-1),old} = \sum_{k=0}^{t-h-2} P_{ik}.$$  

‘New’ Cumulative Quality Improvement Experience ($Q_{i(t-1),new}$) and ‘Old’ Cumulative Quality Improvement Experience ($Q_{i(t-1),old}$) are defined similarly.

3.2.4 Independent Variables for Hypothesis 3

We classified the 2,732 quality improvement initiatives in our research into one of the three types of quality improvement initiatives based on whether they relate to 1) Quality Assurance, 2) Process Improvement or 3) Design Quality. Quality improvement initiatives were classified as ‘Quality Assurance’ if they addressed quality issues by introducing or modifying inspection procedures at vendor facilities, as illustrated in examples 1 through 5 in Table 1. Initiatives were classified as ‘Process Improvement’ if they addressed the quality issues mainly by changes or modifications to the production processes at the vendor facilities, as illustrated in examples 6 through 12 in Table 1. Initiatives were classified as ‘Design Quality’ if they involved changes or modifications to the design of components manufactured by vendors, as illustrated in examples 13 and 14 in Table 1. The classification was done by 20 engineers of the SIU and then the production and quality chiefs at AMC validated the classifications independently. The kappa statistic of inter-rater 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. If there were differences in the classification, then they were resolved jointly by the two chiefs. Overall, there are 458, 2,025, and 249 quality improvement initiatives that relate to quality assurance, process improvement, and design quality respectively. We use this classification to decompose our measure for induced learning $Q_{it}$ into three components to form the independent variables to evaluate Hypothesis 3:

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 done at vendor $i$ in period $t$.  

3.2.4 Independent Variables for Hypothesis 3
‘Lagged Cumulative Process Improvement \((R_i(\hat{t}-1))\)’ and ‘Lagged Cumulative Design Quality \((D_i(\hat{t}-1))\)’ – These are defined analogously.

3.2.5 Independent Variables to Evaluate Hypothesis 4

To evaluate Hypothesis 4, we identify quality improvement initiatives that mainly focus on technology, routines and organizational members. Quality improvement initiatives were classified as ‘Technology Solutions’ if they addressed the quality issues mainly by introduction of new equipment or modifications to existing equipment or processes, as illustrated in examples 1, 2, 3, 6, 7, 8, 13 and 14 in Table 1. In line with Nelson and Winter (1982), initiatives that sought to improve quality performance by changes to repetitive patterns of work or by introduction of repetitive activity at vendors, as in examples 4, 5, 9, and 10 in Table 1, were identified as ‘Routines Solutions’. Initiatives which mainly addressed quality issues by developing operator skills (via training and monitoring), as illustrated in examples 11 and 12 in Table 1, were identified as ‘Operator Solutions’. To do the classification, the vendor development and quality chiefs at AMC jointly identified three examples each of quality improvement initiatives that could be classified as ‘Technology Solutions’, ‘Routines Solutions’ and ‘Operator Solutions’. These examples served as the basis on which 6 SIU engineers undertook the classification for the 2,732 quality improvement initiatives. The resulting classification was validated independently by the vendor development and quality chiefs at AMC. The kappa statistic of inter-rater agreement between these two raters is 0.72, which indicates substantial agreement (Landis and Koch 1977). Differences in the classification were resolved jointly by the two chiefs. In our data, 1,353, 1,067, and 312 quality improvement initiatives were classified as ‘Technology Solutions’, ‘Routines Solutions’, and ‘Operator Solutions’ respectively. This classification enables us to decompose our measure for induced learning \(Q_{it}\) into three components that form the independent variables we use to evaluate Hypothesis 4:

**Lagged Cumulative Technology Solutions**– This is the number of ‘Technology Solutions’ initiatives undertaken at a vendor. It is 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.

3.2.6 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 a specific vendor, and therefore the vendor-level fixed effects also control for the specific engineer. Note that the fixed effects controls in our panel dataset 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 between two to four car models every month. During this time there were three model changes. Therefore, we include indicators to account for the changes in product mix and model changes, in line with Thompson (2007).

**Time Fixed Effects** – Monthly fixed effects control for factors that change over time, such as technology. Tables 2 and 3 provide the descriptive statistics and correlations for our data.

### 4. Methodology

We verify the impact of autonomous and induced learning on 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

We use econometric models that relate quality performance to the drivers of organizational learning: autonomous learning is linked to cumulative production volume, and induced learning is linked to cumulative quality improvement initiatives. The underlying assumption in our models is that vendors develop knowledge that enables them to improve their quality performance. Following Li and Rajagopalan (1998), we assume that such knowledge is gained through production experience or quality improvement experience. We represent the knowledge stock \( K \) for a vendor by:

\[
K = \alpha_1 P + \alpha_2 Q
\]

where \( P \) and \( Q \) represent production and quality improvement experience. We depict the defect rate of a vendor \( Y(K) \), as a function of the knowledge stock. We assume that the vendors and AMC (through the 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 \( \mu \) denotes the learning rate, then the rate of defect reduction can be represented by the differential equation:

\[
\frac{dY(K)}{dK} = \mu [Y(K) - Y']
\]
In line with the larger body of TQM literature (e.g. Deming 1986), we assume that the optimal target rate for defects \( Y^* \) is zero defects. This assumption also aligns with AMC and its vendors because their target is zero defects. The solution to the differential equation (2) gives:

\[
Y(K) = \exp(\alpha + \mu K) \tag{3}
\]

which links quality performance to the knowledge stock. Note that (3) represents the exponential form of the learning curve, 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 \( \epsilon_{it} \) 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. We expect \( \beta_p \) and \( \gamma_Q \) to be negative and significant, indicating that both autonomous and induced learning contribute to lower defect rates. We estimate the econometric 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: estimating model (4) assuming errors arise from an AR(1) process provides similar results). The results of this analysis are shown in model (L1) of Table 4.

An underlying assumption in model (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 \( \lambda_p \) and \( \lambda_Q \) 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 \( AK_{i(t)} \) 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 \( AK_{i(t)} = \lambda_p AK_{i(t-1)} + p_{it} \). Here, we restrict \( \lambda_p \) by the expression \( 0 \leq \lambda_p \leq 1 \), to ensure that depreciation of knowledge is not greater than the existing stock of knowledge. Similarly, the stock of induced knowledge \( IK_{i(t)} \) can be represented as \( IK_{i(t)} = \lambda_Q IK_{i(t-1)} + q_{it} \) where \( 0 \leq \lambda_Q \leq 1 \). We use these parameters to assess the impact of organizational forgetting in the following econometric 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 \( AK_{i(t)} = \lambda_p AK_{i(t-1)} + p_{it} \) 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 (5). If \( 0 \leq \lambda_p, \lambda_Q < 1 \), then it indicates that some knowledge gained from autonomous and induced learning depreciates and is not available in the current period.
The econometric 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 the organizational forgetting parameters $\lambda_P$ and $\lambda_Q$. Consequently, we cannot use traditional linear regression models as they will be unable to provide separate estimates of $\beta_P$, $\gamma_Q$, $\lambda_P$, and $\lambda_Q$. To address our estimation problem of recovering the parameters with their standard errors, we use an approach that builds on the nonparametric bootstrap technique proposed by Freedman (1981) and discussed in Davidson and MacKinnon (2006). In brief, our approach involves two simultaneous steps: (i) a two-dimensional grid search over $\lambda_P$ and $\lambda_Q$ and (ii) bootstrapping. In the grid search step, we calculate the values of autonomous and induced knowledge stock ($AK_i(t-1)$ and $IK_i(t-1)$) for each value of $\lambda_P$ and $\lambda_Q$ 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 $\lambda_P$ and $\lambda_Q$. In the bootstrapping step, for given values of $\lambda_P$ and $\lambda_Q$, 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 dataset. We estimate the regression parameters and the model $R^2$ using the simulated dataset. We repeat this process for all potential values of $\lambda_P$ and $\lambda_Q$ and store the parameter estimates of $\alpha_i$, $\beta_P$, $\gamma_Q$, $\eta_i$, $\phi_i$ and $\psi_i$ and the corresponding values of $\lambda_P$ and $\lambda_Q$ 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 1000 bootstrap replicates as the relevant estimates for our model (5). These results are shown in model (F1) in Table 4. (Additional details of our approach are included in the online appendix A.) Our method builds on the approach used in the organizational forgetting literature by Boone et al. (2008). While they obtain the 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 of Different Modes of Organizational Forgetting

To evaluate Hypothesis 2, we modify the experience variables to identify ‘new’ and ‘old’ components of experience. This allows us to examine the different modes of organizational forgetting as follows:

a. If the ‘old’ components of experience depreciate, then they provide evidence that ‘degradation’,
the mechanism by which established knowledge is not maintained is present.

b. If the ‘new’ components of experience depreciate, then they provide evidence that ‘dissipation’, the mechanism by which new knowledge fails to get consolidated is present.

c. If the ‘new’ components of experience exhibit learning, then they provide evidence that ‘purg- ing’, the mechanism by which vendors ‘unlearn’ processes that cause quality issues and improve their quality performance is present.

We define ‘new’ experience as the experience gained in the last ‘h’ months and ‘old’ experience as the cumulative experience gained prior to the last ‘h’ months, as detailed in section 3.2.3, to obtain:

\[
\ln(Y_{it}) = \alpha_i + \beta_{old} P_{l(t-1),old} + \beta_{new} P_{l(t-1),new} + \gamma_{old} Q_{l(t-1),old} + \gamma_{new} Q_{l(t-1),new} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}
\]  

(6)

Here, \(\beta_{old}\) and \(\gamma_{old}\) capture learning rates for ‘old’ experience, while \(\beta_{new}\) and \(\gamma_{new}\) denote the learning rates for ‘new’ experience.

To examine the depreciation for ‘new’ and ‘old’ components of experience, we define the organizational forgetting parameters \(\lambda_{P,old}\) and \(\lambda_{Q,old}\) to represent the proportion of ‘old’ autonomous and induced knowledge from past periods that is available in future periods, and parameters \(\lambda_{P,new}\) and \(\lambda_{Q,new}\) to represent the proportion of ‘new’ knowledge from past periods that is available in future periods. Consequently, the stock of ‘new’ autonomous knowledge is defined as \(AK_{i(t-1),new} = \sum_{k=t-h}^{t-1} (\lambda_{P,new})^{t-1-k} p_{ik}\), and the stock of ‘old’ autonomous knowledge is defined as \(AK_{i(t-1),old} = \sum_{k=t-h}^{t-2} (\lambda_{P,old})^{t-2-k} p_{ik}\). Analogously, we define the stock of ‘old’ induced knowledge \(IK_{it,old}\) and ‘new’ induced knowledge \(IK_{it,new}\). Based on these we develop the following model to examine the depreciation for ‘old’ and ‘new’ components of experience:

\[
\ln(Y_{it}) = \alpha_i + \beta_{old} AK_{i(t-1),old} + \beta_{new} AK_{i(t-1),new} + \gamma_{old} IK_{i(t-1),old} + \gamma_{new} IK_{i(t-1),new} + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it}
\]  

(7)

To identify the appropriate number of months ‘h’ to be considered for ‘new’ experience, we estimated our econometric specification (6) for values of ‘h’ from 1 through 6 using panel data regression. The model with \(h = 3\) provided the best fit (as measured using \(R^2\) values). The results of this analysis are shown in model (L2) of Table 4. We then evaluated our econometric model (7) using an approach similar to the one used for the evaluation of model (5). These results are shown in model (F2) in Table 4.

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

To evaluate how experience of different types of quality improvement initiatives affects quality performance, we use the variables for lagged cumulative quality assurance \(S_{l(t-1)}\), lagged cumulative process improvements \(R_{l(t-1)}\), and lagged cumulative design quality \(D_{l(t-1)}\) to obtain the following model:
\[ \ln(Y_{it}) = \alpha_i + \beta_p P_i(t-1) + \gamma_S S_i(t-1) + \gamma_R R_i(t-1) + \gamma_D D_i(t-1) + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it} \]  

Next, we define parameters \( \lambda_S, \lambda_R, \) and \( \lambda_D \) 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 at vendor \( i \) in time \( t \). Consequently, the stock of induced knowledge related to quality assurance \( KS_{it} \) can be represented as \( KS_{it} = \lambda_S KS_i(t-1) + s_{it} \), where \( s_{it} \) is the ‘Quality Assurance’ initiatives done in the current period and \( 0 \leq \lambda_S \leq 1 \). \( KR_{it} \) and \( KD_{it} \) are also represented analogously. We incorporate these parameters to capture the impact of organizational forgetting in the following econometric model:

\[ \ln(Y_{it}) = \alpha_i + \beta_p AK_{i(t-1)} + \gamma_S KS_i(t-1) + \gamma_R KR_i(t-1) + \gamma_D KD_i(t-1) + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it} \]  

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

We estimated the econometric specification (8) using panel data regression. These results are shown in model (L3) of Table 4. To estimate the econometric specification (9), our approach is similar to the one used for the econometric model (5). We recovered all the organizational forgetting parameters and standard errors for model (9) using nonparametric bootstrap techniques, where we used 1,000 replicates with a four-dimensional grid search over \( \lambda_S, \lambda_R, \lambda_D, \) and \( \lambda_P \) in increments of 0.0001. These results are shown in model (F3) of Table 4.

### 4.4 Models to Evaluate Impact of where Quality Knowledge Gets Embedded

To evaluate Hypothesis 4, 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 econometric specification:

\[ \ln(Y_{it}) = \alpha_i + \beta_p P_i(t-1) + \gamma_{TS} TS_i(t-1) + \gamma_{RS} RS_i(t-1) + \gamma_{OS} OS_i(t-1) + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it} \]  

We define \( \lambda_{TS}, \lambda_{RS} \) and \( \lambda_{OS} \) to represent the proportion of induced knowledge related to cumulative technology, cumulative routines and cumulative operators 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 at time \( t \). This leads to the following econometric specification to capture the impact of organizational forgetting:

\[ \ln(Y_{it}) = \alpha_i + \beta_p P_i(t-1) + \gamma_{TS} KTS_i(t-1) + \gamma_{RS} KRS_i(t-1) + \gamma_{OS} KOS_i(t-1) + \eta_i V_i + \phi_i M_t + \psi_i C_t + \epsilon_{it} \]  

(11)
We estimated the econometric specification (10) using panel data regression. These results are shown in model (L4) in Table 4. We estimated econometric specification (11) using an approach similar to the one used for the estimation of econometric model (9). These results are shown in model (F4) 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 of our Econometric Models

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 models (L1) and (F1) of Table 4. These results indicate that quality performance improves with cumulative production experience and cumulative quality improvement experience. Thus both autonomous and induced learning contribute to enhanced vendor quality performance in our research setting.

In the context of Hypothesis 1a, we refer to model (F1) in Table 4 and find that \( \lambda_P \) 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 \( \lambda_P \) represents monthly depreciation rate). To predict the impact of autonomous learning, we follow the approach proposed in Cameron and Trivedi (2005, pp. 103-104) because we use log-linear models of the general form \( \ln(y) = x'\beta + \epsilon \) and for such models \( E(y_i/x_i) = \exp(x_i'\beta) E(\exp(\epsilon_i)) \). Consequently, as the average annual production for a vendor is 23.52 (1.96×12 months in 100,000 units) we estimate autonomous learning will 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, due to organizational forgetting, autonomous learning reduces defect rates by only 2.66% annually (calculated as \( (1 − 0.1608) \times 3.17 \)).

To evaluate Hypothesis 1b, we refer to model (F1) in Table 4 and find that \( \lambda_Q \) 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% every year. On average 2.52 (calculated as 0.21×12) quality improvement initiatives are implemented in a year at each vendor, consequently we estimate induced learning will 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, due to organizational forgetting, induced learning reduces defect rates by only 6.64% annually (calculated as \( (1 − 0.1317) \times 7.65 \)). Overall, our results indicate that organizational forgetting affects quality gains obtained from both autonomous and induced learning.
For Hypothesis 2 we refer to the models (L2) and (F2) of Table 4. We observe that the coefficient of ‘new’ cumulative quality improvement experience is negative and significant at p<0.01 in both models (L2) and (F2) of Table 4, however the coefficients of ‘new’ cumulative production experience are not significant. These results do not provide conclusive evidence for the presence of ‘purging’ in our setting. Our results also show that ‘dissipation’ is not present in our context, as the estimates of organizational forgetting for ‘new’ autonomous learning $\lambda_{P,\text{new}}$ and ‘new’ induced learning $\lambda_{Q,\text{new}}$ are not significantly different from 1. We also observe that the estimate of organizational forgetting for ‘old’ autonomous learning $\lambda_{P,\text{old}}$ (0.9784) and ‘old’ induced learning $\lambda_{Q,\text{old}}$ (0.9831) are significantly different from 1 at p<0.001. These results provide evidence that depreciation of quality knowledge at vendors in our context is mainly on account of ‘degradation’. Consequently, our results only partially support Hypothesis 2 (as we do not find conclusive evidence for the presence of ‘purging’).

To examine Hypothesis 3, we refer to model (L3) 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 only significant for quality assurance and process improvement initiatives. We now refer to model (F3) and observe that the estimate of organizational forgetting in quality assurance $\lambda_S$ is not significantly different from 1. This suggests that improvement in quality performance driven by quality assurance initiatives does not depreciate over time. However, $\lambda_R$ 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 projects depreciate by 14.32% every year. Additionally, a Wald test indicates that the estimates of $\lambda_S$ and $\lambda_R$ are significantly different from each other at p<0.01. We do not make inferences about organizational forgetting in the context of 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 due to depreciation in process improvement related knowledge.

For Hypothesis 4, we refer to model (L4) in Table 4 to confirm organizational learning for ‘Lagged Cumulative Technology Solutions’, ‘Lagged Cumulative Routines Solutions’ and ‘Lagged Cumulative Operator Solutions’. Then we observe in model (F4) of Table 4 that the estimates of organizational forgetting for lagged cumulative technology solutions ($\lambda_{TS}$) at 0.9923, for lagged cumulative routines ($\lambda_{RS}$) at 0.9873, and for lagged cumulative operators ($\lambda_{OS}$), at 0.9752, are 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 every year. In
contrast, quality gains obtained from quality improvement initiatives that focus on routines and operators depreciate by 14.22% and 26.02%, respectively, every year. Overall our results support Hypothesis 4.

5.2 Robustness Checks

We now discuss the various tests we undertook to address concerns related to the analytical approaches used in our overall analysis and to tackle specific issues in the evaluation of our individual hypotheses.

5.2.1 Tests Related to the Analytical Approaches

We measure defect rates in monthly intervals. It is possible that random fluctuations in vendor defect rates over monthly intervals may affect our results. To address this concern, we aggregated our data over two, three, four, and five month intervals and evaluated the econometric models (4) and (5). The results with quarterly aggregated data are shown in models (L5) and (F5) 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, it is possible that the costs to implement different quality improvement initiatives could differ and influence AMC’s choice of which initiatives to implement. To address this issue, we obtained the costs incurred by AMC for each quality improvement initiative. These costs represent the extent to which the various quality improvement initiatives undertaken by AMC differ. The cost data enabled us to use the cumulative cost of quality improvement initiatives to capture the impact of induced learning in our models (4) and (5). The estimation results for these models are shown in models (L6) and (F6) of Table 5. These results are essentially similar to those obtained in our main models and provide additional support to our findings.

We evaluated our models with an additional control for calendar time, as Levin (2000) and Lapré et al. (2000) suggest that experience can also be a function of elapsed time. These results are shown in models (L7) and (F7) of Table 5. Our results are robust to the inclusion of the control for calendar time.

We used three tests to investigate for 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 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 econometric specifications (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 examined for 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 3, the relatively smaller sample of design quality initiatives could lead to the absence of significant findings. We used two tests to address this issue. First, we restricted our sample to vendors where at least one design quality initiative was done. This reduced sample included information on 94 vendors where design quality initiatives accounted for 17% of the overall quality improvement initiatives. We redid our analysis for this restricted sample and find that our results for design quality initiatives remain essentially the same. Second, we evaluated our learning models with selective over-sampling 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), and we do not find learning effects for design quality initiatives. Additionally, we also 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 the absence of significant findings for design quality initiatives.

In the evaluation of Hypothesis 4, design quality initiatives are encompassed within technology based improvement initiatives, and it is possible that the absence of organizational learning for design quality initiatives may reflect as organizational forgetting for technology focused initiatives. To address this concern, we excluded design quality initiatives from our data and evaluated models (10) and (11) for the restricted data. Our results remain essentially similar.

We also examined whether endogeneity is a concern in our evaluation of Hypotheses 3 and 4. We used a process similar to the one we used to evaluate the endogeneity of the decision to undertake quality improvement initiatives and find that endogeneity is not a concern for Hypotheses 3 and 4.

6. Discussion and Conclusion

Our study contributes by providing insights on the role of organizational forgetting on quality performance. While several studies have shown that organizational forgetting affects productivity improvements and cost reduction obtained from production experience, we extend this to the quality domain. In our setting, we find that 16.08% of quality gains from autonomous learning depreciate every year.
We contribute by demonstrating that organizational forgetting affects gains obtained from induced learning. To the best of our knowledge, our study is the first to do so. In our context, we find that 13.17% of quality gains from induced learning depreciate every year. Our results confirm the conjectures of several scholars that organizational forgetting may affect quality performance. This is an area of theory that has not been fully explored, and our results suggest that theoretical models that link learning and quality could be enriched by incorporating organizational forgetting.

Our results show that the impact of organizational forgetting on quality is lower than that on productivity improvements or cost reduction. We find that the annual depreciation of quality gains ranges from 13.17% to 16.08%, while prior studies have shown an annual depreciation of production experience ranging from 39% in aircraft production (Benkard 2000) to over 90% in automotive assembly (Eppl et al. 1996) and shipbuilding (Argote et al. 1990). Two potential reasons could account for these differences. The first is that quality performance is often well documented and tracked by vendors and AMC. Further, quality improvement initiatives are typically developed after observing quality problems (e.g., Vibration in assembly shroud fan and motor, as in example 9 in Table 1), exploring potential causes (e.g., Solenoid failure due to water ingress, as in example 8 in Table 1), and identifying possible solutions (e.g., arresting rotary movement of inspection gauge, as in example 1 in Table 1). This deliberate process of addressing quality issues probably facilitates a higher retention of knowledge. The second could be the negligible turnover of AMC’s SIU engineers in this period.

In our context, organizational forgetting mainly affects organizational knowledge through degradation: the depreciation of the ‘old’ component of experience. This suggests that it may be prudent for firms to monitor the quality performance of their vendor base periodically, and also periodically revisit critical quality problems that have been addressed in the past.

Our study also contributes by analyzing the impact of organizational forgetting on different types of quality improvement projects. In our context, knowledge depreciation does not happen in all types of improvement efforts. Learning from quality assurance projects does not decay over time, whereas learning from process improvement projects decays over time. Indeed, almost all the depreciation of knowledge or organizational forgetting happens in the knowledge stock related to process improvement projects. Discussions with AMC engineers and vendors indicate that the explicit checks associated with quality assurance initiatives facilitate greater focus in plant operations to meet the desired quality requirements. Furthermore, the usage of test equipment ensures that the quality gains obtained through such projects are sustained over time. On the other hand, some process improvement initiatives may not address all potential causes of the quality problems. For instance, in Table 1, the eighth quality improvement initiative involved an even application of the sealant. Though the application of the sealant was automated, AMC
engineers pointed out that in some instances foreign materials in the sealant might lead to uneven bonding, leading to quality issues.

One must be cautious about drawing inferences from these results. Our results do not imply that firms should implement quality assurance initiatives instead of process improvement initiatives, as in many instances process improvement initiatives may be more suitable to handle quality issues than quality assurance initiatives (e.g., blow holes in castings can be better handled through improved sand preparation than by using x-rays to test each casting). Given the absence of organizational forgetting for quality assurance initiatives, our results suggest that firms could use such initiatives to address critical quality issues. However, firms will need to consider the cost implications of including an explicit quality assurance step in their operations. If firms use 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 do not 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 know-why or an understanding of the root causes and, in line with Laprê 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 which are embedded in technology exhibit lower rates of depreciation (8.86%) as compared to quality improvement initiatives that are embedded in routines (14.22%) or are 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 not all quality issues can be addressed by technology focused initiatives and many a time changes to routines or development of operator skills may be required to solve quality problems. 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.

The approaches used in our study: of classifying projects into different types of quality improvement initiatives; and of identifying where quality knowledge gets embedded, can all be done ex-ante and hence have practical implications for firms. Our findings are also relevant for managers because they provide insight on managing quality improvement and can enable more informed decision making.

There are some limitations in our study which could be overcome in future research. We do not consider the effect of costs incurred by vendors for implementing the quality improvement initiatives. One could envisage a study that uses information on prevention and appraisal costs to provide insight on the
interplay between benefits from quality improvement efforts and costs of such efforts. Also, we do not observe the complete history of production experience. We recognize that there could be potential benefits of observing the entire history of production experience to improve the inferences related to autonomous learning that could be addressed in future studies. In our study, we were not able to observe initiatives that were not implemented at vendors. A study that examines quality improvement efforts that were not implemented at vendors could potentially provide enhanced insights quality management within supply chains. Using field data has enriched our study; however there are also some inevitable limitations as all facets of a field setting cannot be controlled. Though we have used several robustness checks in our analysis, we believe no single study can provide definitive answers on how organizational forgetting affects quality. We hope our work will stimulate further theoretical and empirical work on the role of organizational forgetting in quality improvement.

References
Management Science 37(3) 267-81.
Argote, L. 2013. Organizational Learning: Creating, Retaining and Transferring Knowledge. 2nd ed. Springer, New York, USA.


Figure 1: Evolution of Quality Performance of Vendor #60

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

Figure 2: Evolution of Incoming Quality Performance at AMC

Note: Quality performance is the average quality of components supplied by the 295 vendors of AMC. Defects are measured in ppm. From 2006 to 2009 incoming quality improved by nearly 25%. 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 the proprietary information of the organization that provided the data for their study.
<table>
<thead>
<tr>
<th>Number</th>
<th>Quality Problem Observed at AMC</th>
<th>Quality Improvement Initiative Implemented at Vendor Facilities</th>
<th>Vendor, Technology, Routines, Operators</th>
<th>Type of Quality Initiative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>In rotor machining line, high rejections at profile checking station.</td>
<td>Inspection gauge modified for only rotary movement with no vertical movement. Fixed zero setting.</td>
<td>#170 Technology</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>2</td>
<td>Line assembly problem with FIP in sensor mounting. Diagnosis: Inadequate guide bush length to check hole position.</td>
<td>Guide bush length of inspection pin increased from 15 mm to 22 mm to avoid defective parts from reaching assembly</td>
<td>#59 Technology</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>3</td>
<td>Improper fitment of 12 H8 taper (1:8) diameter of Steering Knuckle with ball-pin diameter of Rack and Pinion Joint.</td>
<td>Inspection gauge replaced by combination gauge. Gauge will be used for checking both 1/8 taper as well as 12H8 diameter.</td>
<td>#276 Technology</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>4</td>
<td>Turbo charger blade damage. Diagnosis: Foreign material entry from air filter to hose.</td>
<td>Millipore test started at hose supplier for sampling inspection</td>
<td>#201 Routines</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>5</td>
<td>Assembly driver seat recliner mechanism failing. Height of the dimple lock from ratchet lever mounting face was 3.1 mm against specification of 3.6 ± 0.1.</td>
<td>Inspection method modified. Dimple height to be checked with respect to the ratchet lever mounting face instead of individual dimple height checking.</td>
<td>#190 Routines</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>6</td>
<td>Shift in 3 mm spring retention hole position due to reverse orientation of lever in drilling.</td>
<td>Poka-yoke done by incorporating stoppers in drilling fixture to prevent fitment in reverse orientation.</td>
<td>#10 Technology</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>7</td>
<td>3rd and 4th gear is shifting hard during trans-axle assembly testing stage.</td>
<td>Cup locator(ø 19.8mm) introduced in chamfering fixture to avoid in-process variation in wall thickness and diameter.</td>
<td># 82 Technology</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>8</td>
<td>Fuel injection pump failure. Diagnosis: Solenoid failure due to water ingress.</td>
<td>Automated rotary fixture for even sealant application in solenoid manufacture.</td>
<td>#140 Technology</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>9</td>
<td>Vibration in assembly shroud fan and motor. Diagnosis: Improper balancing</td>
<td>Process sequence changed. Balancing to be done before shroud assembly with fan and motor.</td>
<td>#99 Routines</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>10</td>
<td>Assembly rear door channels found with twist.</td>
<td>Operation sequence changed. Twist correction done after piercing operation.</td>
<td>#191 Routines</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>12</td>
<td>Capping length variation observed in rubber hose. Diagnosis: Hose and screw variation.</td>
<td>Three categories of hoses and matching screws identified. Operators trained to match hoses with screws in assembly.</td>
<td>#218 Operator</td>
<td>Process Improvement</td>
</tr>
<tr>
<td>13</td>
<td>Breakage on threading of pin. Diagnosis: Stress relieving of threads by flame softening.</td>
<td>Design drawing modified to induction hardening of working surface of pin, keeping threads soft.</td>
<td>#10 Technology</td>
<td>Design Quality</td>
</tr>
<tr>
<td>14</td>
<td>Rear wiper nozzle discoloration. Diagnosis: Material not UV stable.</td>
<td>Raw material changed to a UV stable material. Design drawing modified.</td>
<td>#288 Technology</td>
<td>Design Quality</td>
</tr>
</tbody>
</table>
Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Log (Defects)</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Production Experience</td>
<td>1.96</td>
<td>9.49</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td>(3) Quality Improvement Experience</td>
<td>0.21</td>
<td>0.93</td>
<td>0</td>
<td>26</td>
</tr>
<tr>
<td>(4) Process Improvement</td>
<td>0.15</td>
<td>0.72</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>(5) Quality Assurance</td>
<td>0.04</td>
<td>0.25</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>(6) Design Quality</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>(7) Technology Solutions</td>
<td>0.17</td>
<td>0.54</td>
<td>0</td>
<td>22</td>
</tr>
<tr>
<td>(8) Routines Solutions</td>
<td>0.16</td>
<td>0.54</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>(9) Operator Solutions</td>
<td>0.07</td>
<td>0.30</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>

* 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.

Table 3: Correlations

<table>
<thead>
<tr>
<th></th>
<th>(1) Log (Defects)</th>
<th>(2) Lagged Cumulative Production Experience</th>
<th>(3) Lagged Cumulative Quality Improvement Experience</th>
<th>(4) Lagged Cumulative Process Improvement</th>
<th>(5) Lagged Cumulative Quality Assurance</th>
<th>(6) Lagged Cumulative Design Quality</th>
<th>(7) Lagged Cumulative Technology Solutions</th>
<th>(8) Lagged Cumulative Routines Solutions</th>
<th>(9) Lagged Cumulative Operator Solutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlations</td>
<td>1.00</td>
<td>-0.20</td>
<td>0.18</td>
<td>1.00</td>
<td>0.17</td>
<td>-0.07</td>
<td>-0.18</td>
<td>-0.19</td>
<td>-0.14</td>
</tr>
<tr>
<td>(1) Log (Defects)</td>
<td>1.00</td>
<td>-0.20</td>
<td>0.18</td>
<td>1.00</td>
<td>0.17</td>
<td>-0.07</td>
<td>-0.18</td>
<td>-0.19</td>
<td>-0.14</td>
</tr>
<tr>
<td>(2) Lagged Cumulative Production Experience</td>
<td>-0.20</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Lagged Cumulative Quality Improvement Experience</td>
<td>0.18</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) Lagged Cumulative Process Improvement</td>
<td>1.00</td>
<td>-0.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Lagged Cumulative Quality Assurance</td>
<td>0.17</td>
<td>-0.07</td>
<td>-0.40</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Lagged Cumulative Design Quality</td>
<td>0.01</td>
<td>0.07</td>
<td>-0.40</td>
<td>0.28</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) Lagged Cumulative Technology Solutions</td>
<td>-0.18</td>
<td>0.12</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(8) Lagged Cumulative Routines Solutions</td>
<td>-0.19</td>
<td>0.20</td>
<td>-</td>
<td>-</td>
<td>0.70</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(9) Lagged Cumulative Operator Solutions</td>
<td>-0.14</td>
<td>0.14</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.75</td>
<td>0.68</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>
Table 4: Estimation Results for the Econometric Models to Evaluate Hypotheses 1 to 4

<table>
<thead>
<tr>
<th>Hypothesis 1</th>
<th>Dependent Variable: Log (Defect Rate)</th>
<th>Modes of Organizational Forgetting (H2)</th>
<th>Impact for Different Types of Quality Improvement Initiatives (H3)</th>
<th>Impact of Where Quality Knowledge Gets Embedded (H4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main Models (H1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(L1)</td>
<td>(F1)</td>
<td>(L2)</td>
<td>(F2)</td>
</tr>
<tr>
<td>Lagged Cumulative Production Experience ($\beta_P$)</td>
<td>-0.0014 (0.000) ***</td>
<td>-0.0017 (0.000) ***</td>
<td>-0.0013 (0.000) ***</td>
<td>-0.0017 (0.000) ***</td>
</tr>
<tr>
<td>Organizational Forgetting for Autonomous Learning ($\lambda_{PA}$)</td>
<td></td>
<td>1</td>
<td>0.9855 (0.005) **</td>
<td></td>
</tr>
<tr>
<td>Lagged Cumulative Quality Improvement Experience ($\gamma_Q$)</td>
<td>-0.0316 (0.006) ***</td>
<td>-0.0383 (0.007) ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Forgetting for Induced Learning ($\lambda_{QI}$)</td>
<td></td>
<td>1</td>
<td>0.9883 (0.004) **</td>
<td></td>
</tr>
<tr>
<td>Hypothesis 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>'Old' Cumulative Production Experience ($\beta_{old}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Forgetting for 'Old' Autonomous Learning ($\lambda_{oldPA}$)</td>
<td></td>
<td>1</td>
<td>0.9784 (0.000) ***</td>
<td></td>
</tr>
<tr>
<td>'New' Cumulative Production Experience ($\beta_{new}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Forgetting for 'New' Autonomous Learning ($\lambda_{newPA}$)</td>
<td></td>
<td>1</td>
<td>1 (0.000)</td>
<td></td>
</tr>
<tr>
<td>Hypothesis 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Cumulative Quality Assurance ($\gamma_S$)</td>
<td>-0.0922 (0.026) ***</td>
<td>-0.0996 (0.029) ***</td>
<td>-0.0251 (0.009) ***</td>
<td>-0.0282 (0.013) *</td>
</tr>
<tr>
<td>Organizational Forgetting for Quality Assurance ($\lambda_S$)</td>
<td></td>
<td></td>
<td>1</td>
<td>0.9994 (0.011)</td>
</tr>
<tr>
<td>Lagged Cumulative Process Improvement ($\gamma_R$)</td>
<td>-0.0290 (0.008) ***</td>
<td>-0.0351 (0.010) ***</td>
<td>-0.0398 (0.017) ***</td>
<td>-0.0478 (0.015) ***</td>
</tr>
<tr>
<td>Organizational Forgetting for Process Improvement ($\lambda_R$)</td>
<td></td>
<td>1</td>
<td>0.9873 (0.001) ***</td>
<td></td>
</tr>
<tr>
<td>Lagged Cumulative Design Quality ($\gamma_D$)</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Organizational Forgetting for Design Quality ($\lambda_D$)</td>
<td></td>
<td>1</td>
<td>0.9993 (0.028)</td>
<td></td>
</tr>
<tr>
<td>Hypothesis 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Cumulative Technology Solutions ($\gamma_{TS}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Forgetting for Technology Solutions ($\lambda_{TS}$)</td>
<td></td>
<td></td>
<td>1</td>
<td>0.9923 (0.001) **</td>
</tr>
<tr>
<td>Lagged Cumulative Routines Solutions ($\gamma_{RS}$)</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Organizational Forgetting for Routines Solutions ($\lambda_{RS}$)</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Lagged Cumulative Operator Solutions ($\gamma_{OS}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Forgetting for Operator Solutions ($\lambda_{OS}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>6.2082 (0.210) ***</td>
<td>6.2271 (0.213) ***</td>
<td>6.1954 (0.225) ***</td>
<td>6.8539 (0.201) ***</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vendor Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Product Mix and Model Change</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R-Square</td>
<td>0.434</td>
<td>0.438</td>
<td>0.444</td>
<td>0.446</td>
</tr>
<tr>
<td>Number</td>
<td>9224</td>
<td>9224</td>
<td>9224</td>
<td>9224</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001; Values reported are coefficient estimates with standard errors in parentheses. All the organizational learning models (L1, L2, L3, L4) and the organizational forgetting models (F1, F2, F3, F4) are significant at p<0.001. We recovered all parameter and standard errors in models (F1, F2, F3, F4) using nonparametric bootstrap techniques. Results use 1,000 replicates with a grid search over organizational forgetting parameters in increments of 0.0001.
Table 5: Estimation Results with Quarterly Aggregated Data, Experience Measured in Costs, and Controls for Calendar Time

<table>
<thead>
<tr>
<th>Dependent Variable: Log (Defect Rate)</th>
<th>Quarterly Aggregation</th>
<th>Quality Improvement Initiatives Measured in Terms of Costs</th>
<th>Additional Control for Calendar Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(L5)</td>
<td>(F5)</td>
<td>(L6)</td>
</tr>
<tr>
<td>Lagged Cumulative Production Experience ($\beta_P$)</td>
<td>-0.0009 (0.000) ***</td>
<td>-0.0009 (0.001) ***</td>
<td>-0.0013 (0.000) ***</td>
</tr>
<tr>
<td>Organizational Forgetting for Autonomous Learning ($\lambda_P$)</td>
<td>1</td>
<td>0.9847 (0.006) **</td>
<td>1</td>
</tr>
<tr>
<td>Lagged Cumulative Quality Improvement Experience ($\gamma_Q$)</td>
<td>-0.041 (0.012) *</td>
<td>-0.047 (0.015) *</td>
<td>-0.0042 (0.001) ***</td>
</tr>
<tr>
<td>Organizational Forgetting for Induced Learning ($\lambda_Q$)</td>
<td>1</td>
<td>0.9908 (0.002) ***</td>
<td>1</td>
</tr>
<tr>
<td>Constant</td>
<td>6.8995 (1.127) ***</td>
<td>6.7851 (0.229) ***</td>
<td>5.7421 (0.270) ***</td>
</tr>
</tbody>
</table>

Controls

| Vendor Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Product Mix and Model Change | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Calendar Time | No | No | No | No | Yes | Yes |
| R-Square | 0.480 | 0.489 | 0.434 | 0.437 | 0.435 | 0.439 |
| Number | 3074 | 3074 | 9224 | 9224 | 9224 | 9224 |

* p<0.05, ** p<0.01, *** p<0.001; Values reported are coefficient estimates with standard errors in parentheses. All the organizational learning models (L5, L6, L7) and the organizational forgetting models (F5, F6, F7) are significant at p<0.001. We recovered all parameter and standard errors in models (F5, F6, F7) using nonparametric bootstrap techniques. Results use 1,000 replicates with a grid search over organizational forgetting parameters in increments of 0.0001.
Online Supplement

Appendix A. Details of the Approach Used to Obtain Organizational Forgetting Parameters

The estimation method we use for recovering parameters and standard errors in model (5) draws on the technical appendix to Boone et al. (2008) who use a one dimensional grid search to estimate the parameters in their models. We extend their approach to two (and higher) dimensions. In what follows, we explain the two dimensional grid search algorithm. Grid searches in higher dimensions are straightforward loop extensions of steps 3 and 4 in the algorithm. Our econometric model (5) is as follows:

\[
\ln(Y_{it}) = \alpha_i + \beta_P AK_{it(t-1)} + \gamma_Q IK_{it(t-1)} + \eta_i V_{it} + \phi_i M_t + \psi_i C_t + \epsilon_{it}
\]  

(5)

where \(AK_{it} = \lambda_P AK_{i(t-1)} + p_{it}\), and \(IK_{it} = \lambda_Q IK_{i(t-1)} + q_{it}\). Our estimation involves recovering the values and standard errors of the parameters \(\alpha_i, \beta_P, \gamma_Q, \eta_i, \phi_i, \psi_i\) for values of \(\lambda_P \) and \(\lambda_Q\) which maximize the likelihood function. Our procedure involves two simultaneous steps: (i) a grid search over \(\lambda_P\) and \(\lambda_Q\) and (ii) a bootstrap to recover the standard errors. The details of this estimation procedure are:

1. For each value of \(\lambda_P\) and \(\lambda_Q\) within the search interval \([0,1]\), given the increment chosen for the grid search, calculate the knowledge terms \(AK_{it}\) and \(IK_{it}\). For example, if the increment chosen is 0.5, we would calculate \(AK_{it}\) using values of \(\lambda_P\) equal to 0.5 and 1, and calculate \(IK_{it}\) using values of \(\lambda_Q\) equal to 0.5 and 1. In our case, we used a grid search increment of 0.0001, so we calculated \(AK_{it}\) and \(IK_{it}\) for values of \(\lambda_P\) and \(\lambda_Q\) equal to 0.0001, 0.0002, 0.0003, …, 0.9998, 0.9999, 1. Doing this for all the \(t\) periods (\(t=45\) in our dataset), gives us \(L\) (=10000 in our case) vectors of autonomous knowledge measures which we can denote as \(AK_{it(L)}\), and \(L\) vectors of induced knowledge measures which we can denote as \(IK_{it(L)}\). Note that at this point, we do not know which of these \(L\) vectors is the correct vector for the two types of knowledge, since we do not know the right value of \(\lambda_P\) and \(\lambda_Q\).

2. Using the number of replicates chosen (we used 1000 draws), begin bootstrapping by drawing rows of data with replacement from the full set of data. Associated with each bootstrap replicate \(m\) will be the dependent variable vector \(\ln(Y_{it})\), draws from the \(L\) “potentially right” vectors of autonomous knowledge (\(AK_{i(L,M)}\)), and draws from the \(L\) “potentially right” vectors of induced knowledge (\(IK_{i(L,M)}\)).

3. For each bootstrap replicate \(m\), loop over each of the \(L\) potential values of \(\lambda_P\) and \(\lambda_Q\) (and the associated autonomous and induced knowledge data) and calculate the panel data regression estimate of the parameters \(\alpha_i, \beta_P, \gamma_Q, \eta_i, \phi_i, \psi_i\) and the model \(R^2\).

4. After recovering these \(L^2\) sets of parameters, find the set having the highest model \(R^2\). This set represents the best fit for the data, and its associated values of \(\lambda_P\) and \(\lambda_Q\) are the estimated depreciation pa-
parameters. Store these parameters for this bootstrap replication, and denote the estimated parameters from replicate $m$ as $\alpha_{im}$, $\beta_{pm}$, $\gamma_{qm}$, $\eta_{im}$, $\Phi_{im}$, $\Psi_{im}$, $\lambda_{pm}$ and $\lambda_{qm}$.

5. Repeat steps 3 and 4 $m$ times (i.e. for each bootstrap replicate).

6. Parameter estimates can now be calculated as the average over $m$ bootstrap replicates, and the standard errors (assuming normality) are also calculated over the $m$ bootstrap replicates. For example, the estimate of model intercept will be $\hat{\alpha} = \frac{1}{m} \sum_{j=1}^{m} \alpha_{ij}$, and the standard error for $\alpha_i$ is $se_\hat{\alpha} = \sqrt{\frac{1}{m} \sum_{j=1}^{m} \frac{(\alpha_{ij} - \hat{\alpha})^2}{m}}$. 