# ESSAYS ON ORGANIZATIONAL LEARNING PROCESSES AND OUTCOMES IN HEALTHCARE

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## ABSTRACT

In my dissertation, consisting of three chapters, I investigate how various mechanisms jointly affect organizational learning in the healthcare sector. The first chapter provides a review of the literature on organizational learning, focusing on how different factors impact four distinct organizational learning processes: search, knowledge creation, retention, and transfer. By categorizing past findings, I identify how the same factor may promote or hinder different organizational learning processes and encourage a more detailed examination of how multiple mechanisms interact to affect organizational learning.

In the second chapter, I examine the relationship between individuals' repeated failures and learning. Through a theoretical framework and empirical analysis of cardiothoracic surgeons in U.S. hospitals, I demonstrate an inverted U-shaped relationship between the number of failures and learning. I find that individuals give up learning after a certain number of failures because their motivation to learn decreases despite increasing learning opportunities. This research aims to reconcile inconsistent findings from the literature on individual failure learning and provides insights into the non-monotonic relationship between failure experiences and individual learning.

In the third chapter, I explore the impact of contractor employment on organizational learning in terms of adopting an industry's new best practices. Using archival data on heart disease patients in U.S. hospitals, where physicians worked as contractors or full-time employees, I find evidence that organizational learning peaks at a moderate proportion of contractors. I theorize that the integration of diverse knowledge held by contractors and firm-specific knowledge held by full-time employees is most effective at this point. This research contributes to the understanding of how a firm's human capital resource composition affects knowledge transfer and organizational learning—an important topic in light of the rising population of contingent workers.

Overall, this dissertation contributes to the literature on organizational learning and the microfoundations of organizational capabilities.

# INTRODUCTION

Organizational learning is crucial in gaining a competitive advantage. However, facilitating organizational learning can be challenging due to the existence of multiple mechanisms that can offset each other's effects, obscuring their combined impact on learning. This dissertation, consisting of three chapters, addresses these challenges by investigating how various mechanisms interact to influence organizational learning, particularly in the healthcare sector. By jointly examining different learning processes—such as opportunity, motivation, and ability to learn—this research provides a more nuanced understanding of promoting organizational learning in healthcare, which can lead to better patient care, benefit healthcare organizations, and contribute to the national economy.

This dissertation employs a mixed-method approach, combining quantitative panel data analysis using unique datasets constructed by merging several manually collected archival data in healthcare with qualitative data collected from interviews with surgeons and physicians. By doing so, this research offers a unique perspective on how individuals learn in organizations and how different mechanisms jointly affect organizational learning, allowing managers and healthcare workers to develop effective strategies to promote learning in their organizations.

Overall, this dissertation makes significant contributions to research on organizational learning and the microfoundations of organizational capabilities. By examining various mechanisms that affect knowledge creation and transfer at the individual level, this research advances our understanding of how individuals learn in organizations, an important microfoundation of organizational learning. Additionally, by investigating how different mechanisms jointly affect organizational learning, this research provides insight into the conditions under which organizations learn effectively, facilitating the development of actionable plans to promote learning in organizations.

# CHAPTER 1. ORGANIZATIONAL LEARNING PROCESSES AND OUTCOMES: MAJOR FINDINGS AND FUTURE RESEARCH DIRECTIONS

**Abstract:** We trace the evolution of research on organizational learning. As organizations acquire experience, their performance typically improves at a decreasing rate. Although this learning-curve pattern has been found in many industries, organizations vary in the rate at which they learn. In order to understand this variation, we separate organizational learning into four processes—search, knowledge creation, knowledge retention, and knowledge transfer. Within each process, we present research on how dimensions of experience and of the organizational context affect learning processes and outcomes. Our goals are to describe major findings and to identify opportunities for future research. The article concludes with a discussion of research directions that are likely to be productive in the future. These directions include investigating how new technological and organizational developments are likely to affect organizational learning.

## 1.1 Introduction

Large increases in productivity typically occur as organizations gain experience in production. This phenomenon is referred to as a learning curve, an experience curve, a progress curve, and learning by doing. Learning curves have been found to characterize not only the production of a wide range of products, including trucks (Epple et al. 1996), semiconductors (Hatch and Mowery 1998), hardware components (Egelman et al. 2017), and chemicals (Lieberman 1984), but also the launch of new products (Gopal et al. 2013) and the establishment of new manufacturing facilities (Salomon and Martin 2008). Learning curves have also been demonstrated in service and knowledge-intensive industries, such as medical care (Bhargava and Mishra 2014, Ibanez et al. 2017, Pisano et al. 2001, Reagans et al. 2005), software development (Boh et al. 2007), and Biotech (Jain 2013). The productivity gains associated with learning by doing are typically very large (Levitt et al. 2013).

Research on organizational learning accelerated in the early 1990s. Because the 1980s were a time of great concern about productivity in the United States (Krugman 1991), understanding sources of productivity gains—such as learning—received increasing attention. We focus on research published since 1990 in our review. Management Science has published much of this research, which has been conducted by researchers in different disciplines, including organizational theory, operations management, strategic management, economics, and engineering. Our focus is on empirical research. We include key results from other sources and other methods, such as computational models, when they advance understanding of organizational learning. Our intent in reviewing the literature is not to be exhaustive but rather to identify current themes, major findings, and opportunities for future research.

We begin with a historical overview of research on organizational learning. We then present major findings and identify current research themes. Our review is organized according to the learning processes of search, knowledge creation, knowledge retention, and knowledge transfer. Within each section, we discuss how dimensions of experience and of the organizational context affect the learning processes and outcomes as well as research opportunities. We conclude with a discussion of promising research directions for the future. These directions include understanding how new technological and organizational developments, such as machine learning and business platforms, are likely to affect organizational learning.

**1.2 Historical Overview of Research**

Psychologists discovered learning curves at the individual level more than 100 years ago. Focusing on the behavior of individuals, psychologists found that the more individuals practiced a task, the less time they took and the fewer errors they made (Ebbinghaus 1885/1964, Thorndike 1898, Thurstone 1919). Shapira (2020) provides an overview of research on individual learning from these early studies to the current day.

While early work on individual learning focused on reinforcement learning from direct experience, Bandura (1971) argued that most learning by individuals occurs through exposure to "social models," examples of other individuals. As Bandura noted, relying on differential reinforcement of trial-and-error behavior to shape desired responses is not feasible in areas where mistakes are costly and/or tasks are complex. Social learning can occur through observation of other individuals performing the task or through instruction about how to perform the task. Social learning has been an active research area with a particular focus on learning from "peers" in educational settings (see Epple and Romano 2011, for a review). Researchers have also examined how social learning can occur in commercial organizations. Exploiting a department store's pseudo-random assignment of staff, Chan et al. (2014) analyzed how peers affected the productivity of individual salespeople in a store's cosmetics department. Each brand of cosmetics operated a different counter and hired its own salespeople, which permitted the investigation of learning from peers at the same counter and learning from peers at different counters as well as learning from the salesperson's own direct experience. Although all three forms of learning were significant predictors of individual sales revenue, learning from high ability peers at the same counter was more important than learning from peers at adjacent counters or learning from one's own direct experience.

Although social learning by individuals can contribute to organizational learning, organizational learning is more than the aggregation of individual learning curves. Most organizations have some division of labor, which results in individuals performing different tasks. The performance of certain tasks (e.g., in engineering) could contribute more to learning at the organizational level than the performance of other tasks. Further, because members of organizations are interdependent, learning how to coordinate members' activities is a critical part of organizational learning. Consistent with the importance of learning to coordinate, Reagans et al. (2005) found that individual, team, and organizational experience all contributed to the learning curves of surgical teams. Individuals got better at performing their particular tasks as they gained experience with the procedure. As team members gained experience working together, they learned how to coordinate their interdependent activities. As the hospital performed more procedures, the time to perform each procedure decreased. The last effect could reflect social learning between teams, a topic that we return to in our discussion of knowledge transfer.

Wright (1936) published the first evidence of a learning curve at the organizational level of analysis. He demonstrated that the amount of labor required to produce an aircraft decreased at a decreasing rate as the organization produced more aircraft. Much of the research on organizational learning curves between the publication of Wright's classic article in 1936 and the 1980s focused on investigating the functional form of the relationship between the unit cost of production and experience measured by cumulative output (Yelle 1979) and on extending the analysis of learning to different products. Learning curves were found to characterize the production of both discrete products, such as aircraft (Alchian 1963), and products made by continuous flow processes, such as petroleum (Hirschmann 1964). Using a production function approach, Rapping (1965) showed that productivity gains associated with experience were not due to greater inputs of labor or capital or to economies of scale. Although early research on learning curves focused on manufacturing industries, researchers are increasingly studying learning in service settings, especially hospitals (Kelsey et al. 1984, Pisano et al. 2001, Reagans et al. 2005).

Learning curve analysis has been used as a tool for managing the operations of organizations as well as for strategic decision making. On the operational side, learning curves can be used for planning (e.g., production schedules, workforce assignments, training, material orders, delivery commitments, budgeting, technology implementations) and monitoring and improving performance (e.g., Arlotto et al. 2013, Carrillo and Gaimon 2000, Dolinsky et al. 1990, Gaimon 1997, Kantor and Zangwill 1991, Levy 1965). Strategically, firms can use learning curves to predict competitors' costs (Henderson 1984), to decide whether to enter a market, and to determine pricing strategy (Balachander and Srinivasan 1998, Raman and Chatterjee 1995). One strategy based on the learning curve is described by Conley (1970), who argued that the firm that produced the most units would have the lowest cost and the greatest profits. That is, firms were advised to build production volume in order to decrease costs and increase profits.

Evidence began to accumulate that learning was more complicated than the relationship between a performance metric and experience. Several high-profile firms failed to follow their expected learning curves. Learning curves are often characterized in terms of a progress ratio, which is defined as the reduction in unit costs associated with each doubling of cumulative output. For example, an 80% progress ratio implies that with each doubling of cumulative output, costs decline to 80% of their previous value. Douglas aircraft did not achieve an 80% progress ratio on its production of the DC-9 (Leonard and Pilarski 2018), which rendered Douglas receptive to an offer from McDonnell. The two firms merged to form McDonnell-Douglas in 1967. Another example of unit costs not following the expected learning curve is Lockheed's production of the L10-11, Tristar, during the 1970s and early 1980s (Argote and Epple 1990). Although Lockheed's costs initially followed a learning curve as cumulative output increased, after production slowed, costs rose and remained higher than the level achieved before the slow down for the rest of the production program (Benkard 2000). The Lockheed case suggested that the knowledge acquired from learning might not be cumulative, as the classic learning curve implied, but rather decay or depreciate.

A review revealed considerable variation in the rate at which organizations learned. Dutton and

Thomas (1984) plotted a histogram of the progress ratio found in more than 100 production programs in manufacturing organizations in different industries (see Balasubramanian and Lieberman 2010, for a similar analysis at a later date). While all but one firm evidenced a reduction in unit costs with experience, the extent of reduction varied widely, ranging from the very rapid progress ratio of 55%, which indicated that costs declined to 55% of their previous value with each doubling of cumulative output, to a progress ratio of 96%, which indicated only a 4% reduction. The modal progress ratio was 81 to 82%. Further, Dutton and Thomas (1984) noted that there was often more variation in progress ratios between organizations within the same industry than between industries. Several subsequent empirical studies found evidence of variation in learning rates across plants within the same organization producing the same product (Argote and Epple 1990, Chew et al. 1990, Hayes and Clark 1986). The variation across units of an organization suggests that knowledge transfer is not automatic and can be challenging to achieve. If knowledge transfer were easy to achieve, the performance of poor performing organizational units should converge to the performance of the better performing units.

Examining the processes of organizational learning provides insights into why the strategy of building the most units in order to achieve the lowest costs and the greatest profits might not be effective. First, if knowledge transfers or "spills over" across firms in an industry, the advantages of increasing production volume are less than when the transfer does not occur because other firms benefit from the knowledge a focal firm acquires. Cho et al. (1998) argued that knowledge transfer helps explain how Samsung, a Korean firm that produced semiconductors, was able to beat competitors in the production of dynamic random-access memory (DRAM), even though its levels of cumulative output were less than those of competitors in the United States and Japan.

Second, if knowledge depreciates, the benefits of cumulative production are less than when knowledge persists through time. Knowledge depreciation could have contributed to Samsung's ability to achieve preeminence in a semiconductor product, DRAM, even though its cumulative output levels were less than those of firms in the United States and Japan. When depreciation occurs and recent output is more important than cumulative output, a new entrant to the industry would not be at a competitive disadvantage if its recent output were comparable to the recent output of competing firms.

Research on organizational learning occurred in parallel to research on organizational learning curves until the 1980s. Two streams existed within the organizational learning research. One stream, most associated with Argyris, focused on the defensive routines members of organizations often invoke that prevent learning (Argyris 1990). Another stream, most associated with March (Cyert and March 1963), emphasized how organizations encode lessons from experience into routines that guide future performance. Levitt and March (1988) published an influential theory piece in this latter tradition in 1988.

These streams of organizational learning research and research on organizational learning curves comingled to some extent in the 1990s. The organizational learning research provided insights into the processes through which learning occurred and, thus, was relevant to understanding the variation observed in learning rates in firms. The organizational learning curve provided a framework for analyzing the effect of various processes on performance. While work on organizational learning up to the 1980s relied mainly on case studies or simulations, later work tested theory on empirical data collected from the field and accounted for issues such as endogeneity that can arise in naturalistic data (Miner and Mezias 1996).

## 1.3 The Organizational Learning Cycle

### 1.3.1 Dimensions of Experience

Learning begins with experience. By experience, we mean a unit of task performance (e.g., performing a surgical procedure). The organization interprets the experience to create knowledge. The interpretation of experience can be challenging and subject to biases, such as "superstitious learning"—a situation in which "the subjective experience of learning is compelling, but the connections between actions and outcomes are misspecified" (Levitt and March 1988, p. 325).

Researchers have characterized experience along different dimensions because different types of experience have been found to have different effects on organizational learning (Argote et al. 2003). Perhaps the most fundamental dimension of experience is whether the experience is acquired directly by the focal unit or indirectly from the experience of another unit. Learning from others is discussed in the section of knowledge transfer. We focus on dimensions of experience that have received attention in the management literature: how novel the experience is, whether the unit of task performance is considered to be a success or failure, how ambiguous the experience is, the temporal dimensions of experience (timing and pace), and its heterogeneity.

### 1.3.2 Organizational Learning Processes

Organizational learning is a process through which experience performing a task is converted into knowledge, which in turn changes the organization and affects its future performance. For analytic purposes, we parse the overall learning process into processes of search, knowledge creation, knowledge retention, and knowledge transfer. The latter three processes were suggested by Argote (2013). To those processes, we add the process of search. Our manuscript focuses on learning within organizations as well as learning by organizations. We include several studies that focus on learning by individuals in organizational contexts, because those studies explicate the mechanisms through which organizational learning occurs. Throughout the manuscript, the term "organization" broadly refers to the units within an organization (e.g., groups, departments, etc.) as well as the organization itself.

The learning processes are interrelated. We illustrate their interrelationship by considering the learning processes from the perspective of a focal organizational unit. Creating knowledge is at the core of organizational learning. An organizational unit can create knowledge from its own experience or vicariously from the experience of other units. For analytic purposes, we discuss studies that focus on learning from an organization's own experience under Knowledge Creation and studies on learning from others' experience in the Knowledge Transfer section. Search processes are intertwined with the creation and transfer of knowledge. Search, which can be internal or external to the focal organization, is aimed at discovering alternatives and their consequences (Cyert and March 1963, March and Simon 1958).

The organizational unit's interpretation of experience results in knowledge. The knowledge can be tacit (Polanyi 1966) or explicit. Retaining knowledge involves embedding it in a repository, such as a routine or a transactive memory system. Knowledge in the various repositories can affect the future performance of the organization. For example, with experience, an organizational unit develops knowledge of who knows what. Because members know whom to consult to solve problems, task performance becomes faster. Thus, experience leads to the knowledge of who knows what, which changes the organizational unit and improves future performance.

Once a focal organization has acquired and retained knowledge, it can transfer it to other units within the organization and/or to other organizations. In addition, knowledge can unintentionally spill over from the focal organization to other organizations in the environment. Transferring knowledge can result in the creation of new knowledge in the unit providing the knowledge as well as in recipient units (Gruenfeld et al. 2000, Miller et al. 2007).

### 1.3.3 The Organizational Context

The context is the set of interrelated conditions that form the backdrop for organizational learning. The context includes both characteristics of the environment external to the focal organization, such as its competitiveness or degree of regulation, as well as internal characteristics of the organization, such as its structure, culture, and identity. The context interacts with experience to affect learning (Argote and Miron-Spektor 2011). Some contexts facilitate learning, whereas others impede it.

Argote and Miron-Spektor (2011) differentiated between (a) the active context and (b) the latent context. The active context includes the basic elements of organizations—members and tools—that interact with the organization's task to influence the interpretation of experience. The latent context, which includes design features of the organization, affects who are members of the organization, what tools they have, and which tasks they perform. A key difference between the active and the latent context is that the active context is capable of action, whereas the latent context is not.

Although individual members are the medium through which most learning occurs in organizations, the capabilities of tools in the form of machines to learn have increased significantly in recent years. Whereas individuals have a general intelligence factor that facilitates performance on a wide range of cognitive tasks, Brynjolfsson and Mitchell (2017) noted that machines do not possess such a general artificial intelligence. Currently, machine learning is most suited for performing particular types of tasks, such as tasks involving learning a function that relates well-defined inputs (e.g., an image in a patient's medical record) to well-defined outputs (e.g., a diagnosis); tasks in which the function linking inputs to outputs does not change rapidly over time; tasks in which large “training” data sets linking inputs to outputs can be created; tasks with clear goals and performance metrics and unambiguous feedback; tasks that do not involve a long chain of logic or depend on taken-for-granted assumptions; tasks that do not require explanations of how decisions were made. In addition to the limits in machines’ capabilities to perform certain tasks, whether machine learning is adopted also depends on social, organizational, strategic, economic and legal factors. Thus, humans are likely to continue to play a major role in organizational learning because they are more effective than machines “at many tasks, especially those that require creative reasoning, nonroutine dexterity and interpersonal empathy” (National Academies of Science, Engineering, and Medicine 2017, p.3)

Knowledge acquired through learning by doing resides in several retention bins or repositories in organizations (Argote and Ingram 2000, Walsh and Ungson 1991). The knowledge repositories include individual employees, the organization’s routines and processes, its tools, its culture, and its transactive memory system of who knows what. Knowledge acquired from learning can be embedded in individual employees, including managers or leaders, engineers and technical support staff, and direct production workers. In order for learning to be organizational, the knowledge an individual acquires would have to be embedded in a supra-individual repository, such as a routine, so that the knowledge would persist in the organization, even if the individual were to depart.

Knowledge can be embedded in the organization’s routines (Cyert and March 1963, Nelson and Winter 1982). A routine is a repetitive pattern of interdependent tasks performed by multiple members of an organization (Feldman and Pentland 2003). For example, as it acquires experience, a hospital emergency unit develops routines for treating patients that embed knowledge about best treatment practices. The routines enable the organization to perform faster and more reliably (Cohen and Bacdayan 1994).

Knowledge can also be embedded in the organization’s tools and culture. For example, as an automotive assembly plant acquires experience, the plant fine-tunes its hardware and software to produce higher quality products. As members acquire experience working together, they develop a shared language or set of common terms (Weber and Camerer 2003), an important aspect of the organization’s culture, that enables members to perform tasks faster and more reliably.

The organization also develops a transactive memory (Wegner 1986) as it acquires experience. A transactive memory system (TMS) is knowledge of who knows what and who is best at what. More formally, a TMS is a collective system for encoding, storing and retrieving information (Lewis and Herndon 2011), which develops from experience working together (Liang et al. 1995) and improves task performance (Ren and Argote 2011). Task assignment is improved because members know who is good at which tasks. Problem solving is also enhanced because members know whom to consult for advice.

We organize our review by the organizational learning processes. Within each process, we first present research on how dimensions of experience affect organizational learning. We then discuss how the organizational context affects learning. We analyze how characteristics of the organization's members (e.g., their diversity or stability) and tools affect and are affected by organizational learning. Next, we discuss how the following contextual features affect organizational learning: the organization's design (e.g., whether it is a specialist or a generalist, its structure, its incentives, its physical layout, its training programs), the organization's culture and norms, its absorptive capacity, its slack resources, its power distribution, and social networks within and across organizations. An article could appear in more than one place in our review because, for example, it examined more than one process or analyzed both the effects of dimensions of experience and the effects of contextual conditions.

**1.4 Search**

Organizational search, the process of seeking solutions to existing or anticipated problems, can result in improving existing organizational routines or capabilities or developing new ones (Cyert and March 1963, Dosi and Nelson 1994, Nelson and Winter 1982). In their behavioral theory of the firm, Cyert and March (1963) introduced the concept of problemistic search, which is stimulated by a problem and aimed at finding a solution. A problem occurs when an organization either fails to achieve at least one of its goals or anticipates such a failure. Goals take the form of aspirations, which are a function of the organization's own previous experience and the experience of "comparable" organizations. Problemistic search occurs when an organization's performance falls below an aspiration level and thus alternatives to current activities are sought. Slack search, on the other hand, occurs when an organization is performing well and has excess resources that allow for experimentation (Levinthal and March 1981). Slack search often occurs far from existing routines and focuses on experimenting with new alternatives that cannot be justified in terms of their expected returns in the short term but could lead to the development of new capabilities in the long run (Levinthal and March 1981). Refinements of the theory have occurred (see Posen et al. 2018 for a review on problemistic search).

Organizational search has also been described in terms of whether the activity contributes to refining existing knowledge or to developing new knowledge. In an influential piece on organizational learning, March (1991) introduced the concepts of exploitation and exploration. Exploitation is related to activities such as “refinement, choice, production, efficiency, selection, implementation, (and) execution,” whereas exploration is related to activities such as “search, variation, risk taking, experimentation, play, flexibility, discovery, (and) innovation” (p. 71). March concluded that organizations need to balance exploitation and exploration activities, which spurred considerable research on the topic (e.g., Andriopoulos and Lewis 2009, Gibson and Birkinshaw 2004, He and Wong 2004).

Finally, organizational search has been described as having various dimensions. For example, Katila and Ahuja (2002) argued that a firm’s search efforts vary across two dimensions: search depth, which refers to how frequently a firm reuses its existing knowledge, and search scope, which is related to how widely a firm explores new knowledge. Focusing only on exploration activities, Rosenkopf and Nerkar (2001) argued that search efforts can occur within a firm or technological boundary or can cross boundaries and categorized search into four types: local, internal boundary spanning, external boundary spanning, and radical search.

### 1.4.1 Dimensions of Experience

**Novelty of Experience.** Novel experiences have been argued to influence search behaviors. For example, Denrell and March (2001) described a “hot-stove” effect, arguing that poor outcomes on a novel decision could lead to avoiding similar choices in the future and redirecting search in directions that might not be optimal. On the contrary, good performance on novel decisions has been shown to reinforce these choices and limit an organization's scope of search to exploitation (Rhee and Kim 2014). Notably, Eggers and Suh (2019) found that responses to negative performance feedback on novel experiences were contingent on an organization's prior domain experience. In the context of U.S. mutual fund companies, firms cease exploration and increase exploitation when they experience negative feedback on new funds launched in new domains, and increase both exploitation and exploration when they experience negative feedback on new funds launched in experienced domains.

**Success vs. Failure Experience.** Performance feedback theory (Greve 2003) suggests that organizations typically regard experience as a success if the performance is higher than the organization's aspiration levels and a failure if otherwise (see Greve and Gaba 2020 for a recent review of research on performance feedback). Aspirations are a function of the organization's own previous experience and the experience of other organizations (see Beckman and Lee 2020 for a recent discussion of how these other organizations or social referents are chosen). Researchers have theorized that the intensity and direction of search depend on the extent to which organizations interpret an experience as a success or failure. In addition, even anticipated future successes or failures can lead to the search for new solutions (Bhardwaj et al. 2006).

It has been shown that organizational performance far above aspiration levels leads to more distant search, in the form of slack search (e.g., Baum et al. 2005, Levinthal and March 1981, Miller and Chen 2004). However, repeated successes have been argued to lead organizations to limit their search for new knowledge (Nelson and Winter 1982, Song et al. 2003). This effect of repeated success on search has been found at the individual level as well, where it has been shown that inventors who have succeeded in the past limit their search space to neighborhoods close to their existing knowledge (Audia and Goncalo 2007). In addition, organizations can fall into "competency traps," where an alternative with known performance properties is preferred over one with uncertain properties (Levitt and March 1988). In this case, organizations might continue to exploit an inferior procedure that led to successful outcomes instead of exploring a potentially superior procedure.

In contrast, when firms are experiencing failures or performing below aspirations, they are likely to engage in problemistic search. Problemistic search initially starts out in the form of local search and refinements in existing knowledge and gradually develops into distant search and explorative search when the initial search efforts are ineffective (e.g., Baum et al. 2005, Billinger et al. 2014, Greve 1998, Levinthal and March 1993, Miller and Chen 2004). For example, Baum and Dahlin (2007) found that performance near aspiration levels triggered local search and exploitation, whereas performance distant from aspiration levels (both far below and above) fostered nonlocal search and exploration. However, when organizations perform extremely poorly, they can actually decrease their level of search (Chen and Miller 2007, Joseph et al. 2016), consistent with the "threat-rigidity" hypothesis (Staw et al. 1981). Desai (2008) found that upon experiencing failures, organizations with less operating experience and poor legitimacy refrain from engaging in search activities that involve risk.

Although the literature suggests that performance both below and above aspirations can increase search efforts, the types of risk involved in search activities might differ under the two situations because organizations have different motivations to search. For example, Xu et al. (2019) found that low-performing firms were more likely to engage in deviant risk-taking behavior (e.g., bribery) to find short-term solutions than high-performing firms. On the other hand, high-performing firms engaged in more aspirational risk-taking behavior (e.g., R&D) to sustain long-term competitive advantage than low-performing firms.

**Ambiguity of Experience**. An experience can be causally ambiguous when the relationship between inputs and outputs of a task is not clear. Ambiguous experiences have been theorized to affect search processes. For example, Rahmandad (2008) showed in a simulation that if the performance feedback from a search activity is delayed and thereby ambiguous, it could cause organizations to abandon such search activity—although there could have been positive organizational returns to sustaining search in the long run.

**Pace of Experience.** There is some evidence that the pace of experience, the rate of which experience occurs, affects search behaviors. For example, Zellmer-Bruhn (2003) found that interruptive events that temporarily prevent the organization from accumulating experience in their normal routines could trigger active cognitive processing that leads to the search for new and better routines. Hayward (2002) similarly found in a study on merger and acquisition experiences of firms that too little time between experiences could limit organizational search capabilities for learning. Interestingly, he also found that too much time between experiences could dampen organizational search as well.

In its extreme form, experience can occur very infrequently. Such rare experiences influence search behaviors as well. Treating an organizational crisis as a rare event, Rerup (2009) found qualitative evidence that such an event can trigger a search for solutions to organizational problems that were not obvious prior to those events. His case study showed that the search for solutions occurred both within the organization (such as reexamining the current organizational structure) and outside of the organization (such as becoming more attentive to the external environment). Christianson et al. (2009) similarly found that rare (and disastrous) events could lead organizations to search for solutions in areas that they would not have considered otherwise.

**Heterogeneity of Experience.** The heterogeneity of experience has been found to influence search behaviors. For example, Haunschild and Sullivan (2002) found that experiencing a variety of failure experiences led to a broader search for solutions to organizational problems than experiencing homogeneous failure experience. Similarly, Kim et al. (2009) found that accumulating both success and recovery experiences led to the search for better solutions, compared to accumulating only success experiences or only recovery experiences. Finally, Zollo (2009) found that accumulating a stock of heterogeneous experience could prevent organizations from engaging in superstitious learning.

### 1.4.2 Organizational Context

**Members.** Individual members' characteristics can influence their tendency to explore versus exploit (Laureiro-Martínez et al. 2010). For example, whether organizational decision makers had career experience in particular business functions (e.g., research and development, marketing, finance, legal, operations) or obtained advanced science-related degrees influenced their tendency to search for new solutions (Barker III and Mueller 2002). In addition, high-ability employees who found it easier to meet minimal performance requirements under a fixed-salary incentive system engaged in more exploration than low-ability employees, presumably to acquire new knowledge and skills using their slack time (Lee and Meyer-Doyle 2017). Finally, Lee (2019) found that individuals with higher organizational tenure were more capable of learning the knowledge and skills of newly co-located organizational peers and utilizing such knowledge and skills to increase exploration than those with lower organizational tenure.

Member diversity and stability have also been found to influence search behaviors because they affect the knowledge and experience base of organizational members. Taylor and Greve (2006) found that teams with members with diverse knowledge and experience produced innovative but high-variance outcomes, presumably because they engaged in more exploratory search. Similarly, March (1991) showed in a simulation that turnover of organizational members can facilitate exploration. Interestingly, Franke et al. (2013) suggested that effective exploratory search can be achieved by bringing in individuals who have expertise in contextually distant domains that share an analogous organizational problem.

**Tools.** The use of tools can also influence search behaviors. Using a simulation model, Kane and Alavi (2007) demonstrated that tools such as knowledge repositories, portals, and virtual team rooms facilitated exploitative search, whereas electronic communities of practice facilitated explorative search. Based on an analytic model, Lee and Van den Steen (2010) concluded that organizations benefit more from a knowledge management system when they are large, experience the same issues repeatedly, have high turnover, and encounter problems about which there is less general knowledge. Kim et al. (2016) found that a knowledge management system implemented in a retail grocery chain assisted managers who had few alternative sources of knowledge to search effectively for solutions to improve store performance. On the other hand, Haas and Hansen (2005) found in a consulting organization that downloading documents from a knowledge repository was associated with poor team performance, especially for experienced teams.

**Specialist vs. Generalist Organizations.** Specialist organizations tend to engage in search that is localized to a particular domain, whereas generalist organizations tend to search more broadly across a variety of domains. Specialists also are likely to search in more depth than generalists (Kang and Snell 2009).

**Organizational Structure.** Organizational structure has been theorized to influence organizational search. Using simulation models, studies have shown that decentralization enables organizations to explore new solutions and thereby prevents them from prematurely converging on suboptimal solutions (Ethiraj and Levinthal 2004, Siggelkow and Levinthal 2003, Siggelkow and Rivkin 2005). In another simulation study, Csaszar (2013) presented results suggesting that reducing hierarchy could promote exploration. Finally, in terms of balancing between exploitation and exploration, Fang et al. (2010) found that organizations divided into semi-isolated subgroups were better at maintaining the balance between exploitative and exploratory search than isolated subgroups or randomly connected individuals.

Empirical studies have yielded results largely consistent with simulation models. For example, Jansen et al. (2006) showed that decentralization increased explorative innovation in organizations. Interestingly, in the context of mergers and acquisitions, Puranam et al. (2006) showed that the immediate structural integration of firms harmed the acquired firm's innovation performance when the acquired firm was in the stage of its innovation trajectory in which exploration was more important than exploitation. However, when the acquired firm was in the stage in which exploitation was more important than exploration, structural integration led to more innovations. Perretti and Negro (2006) found that either having a flat hierarchy or a hierarchy with middle managers who can effectively coordinate interdependencies between different organizational projects led to exploratory search. Jansen et al. (2009) found that structurally differentiated organizations can balance exploitative and exploratory search by adopting integration mechanisms such as senior team social integration and cross-functional interfaces.

A growing stream of research shows that organizational structure moderates the relationship between performance feedback and organizational search. For example, Rhee et al. (2019) found that in hierarchical business groups with multiple sub-units, problemistic search at the sub-unit level is significantly intensified when group-level managers are cognitively aware of the problems at the sub-unit level and provide support for solving such problems. In another study in the context of Indian firms, Vissa et al. (2010) found that business group-affiliated firms and unaffiliated firms respond differently to performance feedback. Business group-affiliated firms were more likely to increase search when they were underperforming in terms of market position compared to unaffiliated firms because business group-affiliated firms' aspiration levels were more externally oriented than those of unaffiliated firms were. In addition, Joseph et al. (2016) found that centralized organizational structures amplify responses to performance feedback above aspirations but attenuate them below aspirations.

Ownership structures also influence organizational search behaviors. For example, Wu (2012) showed that when organizations go public through initial public offerings, they decrease search that explores new and recently developed knowledge but increase search building on scientific knowledge. In addition, O'Brien and David (2014) showed that different types of ownership led to different intensities of search behaviors in response to positive performance feedback.

**Incentives.** Incentive designs have been shown to influence search behaviors. For example, Lee and Meyer-Doyle (2017) showed that switching individuals' incentives from a pay-for-performance system to a fixed-salary system promotes exploratory search. Ederer and Manso (2013) found that an incentive system that tolerates early failure and rewards long-term success is most effective for exploratory search. Using a simulation model, Baumann and Stieglitz (2014) suggested that higher-powered incentives could lead to excessive competition among organizational individuals and thus dampen search efforts.

**Physical Space.** The design of organizational physical space has been also found to influence search behaviors (Allen 1977). For example, Lee (2019) found that reconfiguring seating arrangements so that previously separated individuals are seated closer together led to learning that stimulates exploratory search and also improves the effectiveness of exploitative search. Catalini (2018) showed that colocation between organizational members decreases search costs and promotes novel collaborations. Clement and Puranam (2017) similarly showed in a simulation model that physical separation mandated by a formal organizational structure could limit organizational individuals' search for novel social interactions.

**Organizational Culture and Norms.** Organizational culture influences the pattern of search behaviors of individuals within organizations. Gambeta et al. (2019) found that strong firm-employee relationships led to employees engaging in more exploitation and less exploration. In a study of inventors in the hard disk drive industry, Audia and Goncalo (2007) found that successful individuals working in firms with a norm for exploration (i.e., distant search) were less likely to generate incremental ideas than successful individuals working in firms without such norms.

**Absorptive Capacity.** Absorptive capacity is an organization's "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal 1990, p. 128). Absorptive capacity is gained by accumulating experience, and the higher an organization's absorptive capacity, the more likely it will effectively search for novel solutions externally (Cohen and Levinthal 1990, Rothaermel and Alexandre 2009). For example, in a study on the acquisition behaviors of Ontario nursing home chains, Baum et al. (2000) found that organizations generally search for new solutions in search spaces in which they have prior experience and in spaces in which other large or similar organizations have been actively searching. Several comprehensive reviews on the topic of absorptive capacity have been published (see Lane et al. 2006, Todorova and Durisin 2007, Volberda et al. 2010, Zahra and George 2002).

**Slack Resources.** Slack resources have been characterized as both motivators and moderators of search processes. Several factors, including organizational performance above aspiration and environmental conditions, can affect the development of slack resources in organizations (Sharfman et al. 1988). A search process that is stimulated by slack resources is called a "slack search" (Cyert and March 1963, Levinthal and March 1981). Slack search is commonly characterized as exploratory and occurring in search spaces distant from those related to existing organizational routines and capabilities (Levinthal and March 1981). For example, Iyer and Miller (2008) found that firms with more slack engaged in more acquisitions, an activity that involves risk and distant search. Slack resources have also been found to increase the intensity of search. For example, Chen (2008) found that firms' financial slack increases the R&D intensity of firms. Slack in terms of human resources has also been found to influence organizational search. For instance, Lecuona and Reitzig (2014) found that having slack in human resources who possess tacit and firm-specific knowledge facilitates the search for novel solutions when the firm faces competitive pressures in its external environment.

**Power and Status.** Bunderson and Reagans (2011) suggested that power and status differences between individuals within an organization can lead individuals with lower power or status to engage in less risk-taking and experimentation—activities that are core to exploratory search. Loch et al. (2013) found that power and status differences within a group impaired problem solving because members relied too much on high-status members. Lower-status members in organizations typically have lower levels of psychological safety compared to higher-status members (e.g., Edmondson 2002, Nembhard and Edmondson 2006), which presumably can contribute to the limited search activities of lower-status members. In addition, Singh et al. (2010) found that individuals with low status in organizations typically have poor connectivity with other organizational individuals, which limits their search for new information.

**Social Networks.** Social networks open up opportunities for search. Hansen (1999) found that weak interunit ties in organizations help project teams search for valuable knowledge in other subunits, whereas strong ties were necessary to transfer tacit knowledge. In addition, organizational alliances have been suggested to facilitate distant search (Rosenkopf and Almeida 2003). Moreover, using a simulation model, Lovejoy and Sinha (2010) showed that maximizing the number of parallel conversations per period while encouraging individuals to dynamically churn through a large set of conversational partners fosters the creation of ties that facilitate the search for new solutions. Rogan and Mors (2014) found that the network density and network contact heterogeneity of managers affect their capability to effectively balance exploratory and exploitative search.

Interestingly, not all network ties are useful for effective search. Borgatti and Cross (2003) suggested that the decision to seek information from others depends on relational characteristics between the information seeker and the information source. When the seeker knows the source's expertise, positively evaluates such expertise, and perceives that he or she has access to the information source, he or she is more willing to seek information from that source. Similarly, Singh et al. (2010) found that individuals with higher status, higher tenure, and better connectedness are able to take advantage of network structures more when searching for information than individuals lacking those characteristics. Nerkar and Paruchuri (2005) argued that inventors reduced the cost of search by signals of quality based on their colleagues' positions in networks within the firm. When individuals were central in the communication network and spanned structural holes (Burt 1992), it was more likely that their knowledge would be selected by another inventor. Further, there was some evidence that centrality and structural holes positively reinforced each other.

### 1.4.3 Research Opportunities

Although the effect of success versus failure experience has received considerable research attention, the other dimensions of experience have not been studied much in relation to search. It would be useful to deepen our understanding of the relationship between different dimensions of experience and search. For example, how would organizations shift their search behaviors when faced with ambiguous experience? Would organizations engage in local search to interpret the ambiguous experience using their own expertise or engage in distant search to make sense of the experience using knowledge from new domains? In addition, ambiguous experience can potentially facilitate organizations' exploration. Ambiguous performance feedback from exploration activities might allow organizations to continue to search more distantly instead of ceasing exploration activities when faced with initial negative outcomes, despite the potential of long-term positive outcomes. Further, the relationship between heterogeneous task experience and search merits additional attention. Could moderate task heterogeneity benefit organizational search by encouraging the balance between exploitation and exploration?

Dimensions of the organizational context that warrant more attention in relation to search are (1) characteristics of members, (2) whether the organizations are specialists or generalists, and (3) routines. Specifically, what are the mechanisms driving the different search behaviors of specialists and generalists? Do specialists tend to search more locally because they lack motivation (e.g., less necessary to acquire knowledge outside of their core domains), abilities (e.g., low absorptive capacity in other knowledge domains), or opportunities (e.g., the lack of social networks conducive of acquiring new knowledge)? Further, it would be interesting to consider the role of routines in balancing exploitation and exploration. For example, would it be possible for organizations to develop routines that foster engaging in both exploitation and exploration? Also, how do newcomer socialization processes and organizational norms influence the relationship between member turnover and search behavior? While newcomers can bring new expertise and encourage organizations to search in new domains, if conformity pressure is high, newcomers might instead search extensively in organizations' existing knowledge domains to conform to the new setting.

### 1.5 Knowledge Creation

As organizations perform a task, they acquire knowledge. Members learn how to perform their individual tasks better and learn who is good at which tasks. Tools are calibrated. Routines are refined and structures are fine-tuned. Members interpret whether task performance was a success or failure, which can stimulate search. Thus, performing a task can result in the creation of new knowledge in the organization. We focus in this section on learning from an organization's own direct experience.

### 1.5.1 Dimensions of Experience

**Novelty of Experience**. Research has suggested that organizations could develop a greater amount of knowledge by balancing experience high and low in novelty rather than focusing on one type of experience (March 1991). For example, He and Wong (2004) found that pursuing high levels of both exploitative and explorative innovation strategies increased manufacturing firms' sales growth rate by improving firms' processes and products. Similarly, Katila and Ahuja (2002) showed that firms introduced more new products when they balanced exploitation and exploration.

**Success vs. Failure Experience.** Several studies investigated whether organizations learn differently from their own success and failure experience. Research has found that organizations learn from their own failures (Chuang and Baum 2003, Madsen 2009). For example, Stan and Vermeulen (2013) showed that fertility clinics that had a higher chance to experience failures because they admitted complex cases learned at a faster rate than clinics that admitted only relatively simple cases. Complex cases enabled the clinics to deepen their understanding of knowledge domains, explore new solutions, and develop tools and routines to capture and transfer the knowledge gained from the complex cases. In a study of accidents in U.S. railroads, Baum and Dahlin (2007) found that organizations learned from their own failures when the organizations' performance (i.e., accident rates) did not deviate far from their aspiration levels.

Several studies have focused on identifying the conditions that facilitate organizations' learning from their own failures. Haunschild and Sullivan (2002) showed that specialist airlines learned more from failures with heterogeneous causes than from failures with homogeneous causes. As noted earlier, it is likely that failures with heterogeneous causes triggered organizations to conduct broader search for solutions than failures with homogeneous causes. Studying recalls of automakers, Haunschild and Rhee (2004) found that experience with voluntary—but not involuntary—recalls reduced subsequent involuntary recalls. The researchers suggested that learning from voluntary recalls was much deeper than learning from involuntary recalls, underscoring the role of volition in learning. In the context of hospitals where surgeons perform heart surgeries, Desai (2015) found that organizations learn less from failures when their failures are relatively concentrated in origin, meaning that failures are incurred mostly by a particular organizational unit or a specific member, compared to when failures are more broadly dispersed across units or individuals. Finally, prior studies have suggested that organizations learn more effectively from unexpected or salient failure experiences than from expected or less salient failure experiences (e.g., Madsen 2009, Madsen and Desai 2010, Ocasio et al. 2020, Rerup 2009).

Studies that directly compare the effectiveness of organizations' learning from their own successes and own failures have provided mixed findings. Madsen and Desai (2010) found that organizations learned more effectively from failures than successes. The researchers suggested that failures help organizations identify gaps in organizational knowledge and increase organizations' motivation to fill the knowledge gap. On the other hand, KC et al. (2013) found that individuals within organizations learned from their own successes but not from their own failures. This pattern was suggested to be due to individuals attributing their own successes to internal factors from which they could draw lessons while attributing their own failures to external factors that would not provide generalizable lessons. Kim et al. (2009) found that organizations learned from both successes and failures only after accumulating a certain threshold of success and failure experience. Further, as noted earlier, success and failure experience enhanced learning from the other type of experience because contrasting different types of experience enabled organizations to generate more useful lessons.

On the topic of learning from failures, recent developments have occurred on the methodological front. Bennett and Snyder (2017) proposed a revised method to examine learning from failures, in which they recommend measuring failure experience within a moving time window instead of across an entire sample period, and not including success experience in the same model with failure experience.

**Ambiguity of Experience.** Causally ambiguous experience can hinder learning from an organization's own experience, as it is difficult for organizations to interpret such experience (Levitt and March 1988). A delay between an action and an outcome could make an experience causally ambiguous. Diehl and Sterman (1995) found that teams performed more poorly as the delay in feedback became longer. Similarly, Repenning and

Sterman (2002) showed that the delay in the feedback of a process improvement initiative hindered employees from understanding the effectiveness of the initiative accurately.

**Timing of Experience.** Several studies found that organizations learn not only by doing but also before and after doing. Pisano (1994) found that learning before doing, such as conducting research prior to actual production, was beneficial only when an industry already had a deep knowledge base. In contrast, learning by doing was more useful than learning before doing when the knowledge base was not well developed. Similarly, Eisenhardt and Tabrizi (1995) showed that the computer industry, characterized by an evolving knowledge base, did not benefit from planning before production. Focusing on after-event reviews, Ellis and Davidi (2005) showed that the learning effect was greater when groups were debriefed on both successes and failures than when groups were only debriefed on failures. Furthermore, Morris and Moore (2000) found that individuals could learn by reflecting on how they could have done better after an experience (upward counterfactual comparisons).

One study focused on the life cycle of organizations. Aranda et al. (2017) suggested that mature organizations learn more from their own past experience than from other organizations' experiences because mature organizations have sufficient levels of their own experience from which to draw lessons.

**Pace of Experience.** The rate at which organizations acquire experience can affect their processes of learning from their own experience. For example, acquiring experience at an uneven rate can hinder learning from experience (Argote et al. 1990). Furthermore, although learning from infrequently occurring or rare experience can be challenging, such rare experience can provide organizations with valuable lessons (e.g., Lampel et al. 2009). Focusing on acquisition events, Zollo (2009) suggested that learning from rare experience with ambiguous performance metrics is particularly difficult because organizations are likely to interpret the outcomes as successes and engage in superstitious learning. Rerup (2009) showed that organizations have to invest deliberately to learn lessons from rare experience. Madsen (2009) found that coal miners learned from both frequently occurring minor accidents and rarely occurring disasters, but through different mechanisms. Minor accidents contributed to learning by alarming employees to comply with organizations' safety routines, whereas rare disasters triggered fundamental changes in the organization's safety routines. Similarly, Christianson et al. (2009) found that rare events provided organizations with the opportunity to improve existing routines.

**Heterogeneity of Experience.** Research on the effects of heterogeneous experience on the creation of knowledge has yielded mixed results. Several studies have suggested that heterogeneous task experience could hinder organizational learning and performance. Fisher and Ittner (1999) found that product variety negatively influenced auto plants' productivity. Clark et al. (2018) showed that the organizational learning rate diminished when the goals of heterogeneous tasks were not aligned. Gopal et al. (2013) found that the deleterious effect of manufacturing new heterogeneous products was mitigated when the plant had past experience in producing products that were similar to the new product. On the other hand, other studies have suggested that heterogeneous experience facilitates organizations' learning from their own experience (e.g., Egelman et al. 2017, Narayanan et al. 2009, Schilling et al. 2003, Wiersma 2007). Underscoring the benefits of heterogeneous task experience, Staats and Gino (2012) found that individuals learned how to effectively switch between different tasks as they gained more heterogeneous task experience. In addition, Jeppesen and Lakhani (2010) found that individual problem-solver's experiences in technological or social domains different from the focal problem facilitated developing successful solutions in science problem-solving contests.

These divergent findings on experience heterogeneity can be reconciled by considering the level of analysis at which learning occurs and by considering the degree of heterogeneity. Boh et al. (2007) found that the effect of heterogeneous task experience differed depending on the levels of analysis: individuals benefitted the most from specialized task experience, whereas groups benefitted the most from working on heterogeneous tasks that were related. Schilling et al. (2003) found in a laboratory study that moderate task heterogeneity was beneficial and suggested that performing tasks that are different but related allowed groups to develop a more abstract and deeper understanding of knowledge applicable to different tasks. Egelman et al. (2017) found that the performance of a contract manufacturer was improved when the organization produced multiple generations of the same product family and that knowledge transfer between related products was the mechanism driving the benefit of related product variety. Similarly, in the context of hospitals, Clark and Huckman (2012) found that cardiovascular patient care quality was improved when hospitals also specialized in areas related to cardiovascular care. The authors suggested that the co-specialization enabled cardiovascular specialists to access new knowledge and insights held by specialists of other care units. Thus, the performance of related tasks benefits the performance of a focal task, suggesting that some heterogeneity in experience can be beneficial for task performance.

### 1.5.2 Organizational Context

**Members.** Member diversity has been found to affect organizational learning. For example, in the semiconductor industry, Macher and Mowery (2003) found that team diversity moderated the relationship between experience and organizational performance such that functionally diverse teams learned more from their experience than functionally homogeneous teams.

Several studies examined the effect of team stability on organizational learning. On the one hand, team stability was found to have a positive effect on organizational learning. For example, Reagans et al. (2005) found that team stability (i.e., the average number of times team members worked together) had a positive effect on the performance of surgical teams. Similarly, Huckman et al. (2009) found that team stability positively contributed to the performance of software teams. In the context of a software support services operation, Narayanan et al. (2009) found that new member entry into a workgroup reduced productivity. They also found that productivity suffered when the variety of experience in a workgroup was reduced due to a member exiting. On the other hand, in the context of delivering mail, Wiersma (2007) found that employing a modest level of temporary employees increased organizational learning rates due to the new knowledge that temporary employees brought into the organization.

**Tools.** Tools can positively influence learning by facilitating the acquisition, storage, and sharing of information. Research on the effect of tools on organizational learning has focused mainly on information technology or knowledge management systems. For example, Ashworth et al. (2004) found that the adoption of an information system in a bank increased learning from both direct and indirect experience.

**Specialist vs. Generalist Organizations.** Evidence on whether generalist or specialist organizations learn more effectively is somewhat mixed. Most studies found that specialist organizations learn more from experience than generalist organizations (Haunschild and Sullivan 2002, Ingram and Baum 1997). For instance, in the context of retail banks, Barnett et al. (1994) found that specialist banks had higher returns on assets as a function of experience than generalist banks. In addition, Ingram and Baum (1997) found that organizations that operated over a large geographical area (i.e., "geographical generalists") learned less from their own experience than organizations that specialized in a smaller number of areas. Interestingly, in the context of airlines learning to increase customer satisfaction, Lapré and Tsikriktsis (2006) found that the best specialist airline (i.e., focused airline) learned faster than the best generalist airline (i.e., full-service airline), although there was no difference in learning rates, on average, between the two types of airlines. In the context of hospitals, KC and Terwiesch (2011) examined the effect of the degree of specialization on performance at different levels of analysis. After controlling for the potential effect of selectively admitting easy-to-treat patients, firm-level specialization (e.g., the fraction of cardiac-related admissions among all admissions) did not have a positive effect on patient care quality, whereas operating unit-level specialization (e.g., the fraction of patients with a particular cardiac illness among all cardiac patients) did improve patient care quality. An exception to the pattern of specialist organizations learning more from experience than generalist organizations is provided by Haunschild and Rhee (2004), who found that generalist automobile manufacturers learned more from voluntary product recalls than specialists did.

**Organizational Structure.** Bunderson and Boumgarden (2010) found that in self-managed teams dealing with stable tasks, more team structure (i.e., higher degrees of specialization, hierarchy, formalization) facilitated learning. Stan and Puranam (2017) showed that clinics with integrator structures (e.g., coordinator roles) recovered more quickly from a regulatory shock that shifted the interdependence patterns among employees and had steeper learning rates after the shock than clinics lacking integrator structures. Ben-Menahem et al. (2016) found that both formal coordination structures and informal coordination practices contributed to team-based knowledge creation. Lee (2019) found that organization members became better at both creating new knowledge and refining existing knowledge when their seats were moved closer to seats of individuals from whom they were previously separated. Bresman and Zellmer-Bruhn (2013) found that team- and organizational-level structures had different effects on learning: greater team-level structure was associated with increased internal and external team learning, whereas a greater organizational-level structure was associated with decreased internal and external team learning. Sorenson (2003) found that vertical integration hindered the rate of learning in firms in stable environments and facilitated learning in volatile environments.

**Incentives.** Lee and Meyer-Doyle (2017) found that switching from a pay-for-performance incentive system to a fixed-salary system promoted learning because individuals engaged in more exploration efforts under the later system. Similarly, Lee and Puranam (2017) found that switching from a pay-for-performance incentive system to a fixed-salary system promoted learning through increased knowledge sharing and collaboration between individuals. As noted earlier, Clark et al. (2018) found that the learning curve for surgeons' patient care outcomes was influenced by whether the goals of the other incentivized activities were aligned with improving patient care.

**Training.** The training of individuals or groups within an organization can improve learning (Bell and Kozlowski 2008, Ford 2014). Training is particularly useful when organization members have opportunities to observe experts or experienced members performing tasks (Nadler et al. 2003) because trainees can acquire tacit knowledge through observing experts perform tasks (Nonaka 1991). Studies have also shown that group training is more beneficial than individual training for collective learning (Hollingshead 1998, Liang et al. 1995). "Transactive memory systems"—a collective system for encoding, storing and retrieving information—develop when members are trained in groups. Also characterized as "knowledge of who knows what," transactive memory systems have been found to facilitate the creation of knowledge (Gino et al. 2010).

**Organizational Culture and Norms.** Organizational culture and norms also have been found to influence knowledge creation. For example, Edmondson (1999) found that a culture characterized by "psychological safety" facilitated learning. In psychologically safe environments, members feel safe to express their ideas and take risks (Bunderson and Reagans 2011, Nembhard and Edmondson 2006). When team members emphasize learning in their unit rather than comparing their performance to that of other units, they learn more from their experience (Bunderson and Sutcliffe 2003). Finally, cohesion or liking among group members (Wong 2004) or shared language among organizational members (Weber and Camerer 2003) can also facilitate the interpretation of and learning from their own experience.

**Absorptive Capacity.** Absorptive capacity is determined by the level of prior related knowledge (Cohen and Levinthal 1990), which is accumulated through activities such as research and development (R&D) as well as through training and experience performing the task. R&D has been found to facilitate learning not only from external sources but also from an organization's own direct experience. For example, in the context of the chemical processing industry, Lieberman (1984) found that R&D investments increased the rate of learning among firms. Similarly, Sinclair et al. (2000) found that R&D was associated with the productivity gains observed in a chemical firm.

**Slack Resources.** Slack resources can open up opportunities for creating new knowledge (Cyert and March 1963). Indeed, severalstudies found a positive relationship between organizational slack and organizational learning (e.g., Wiersma 2007). However, other studies found an inverted U-shaped relationship between slack resources and new knowledge creation: increases in slack initially facilitated innovation, but too much slack hurt the discipline necessary to produce innovations (Nohria and Gulati 1996).

**Power and Status.** In a review paper, Bunderson and Reagans (2011) suggested that power and status differences could lead to less collective learning in organizations because such differences hindered experimentation, knowledge sharing, and the development of shared goals. The authors further concluded that these negative effects could be mitigated when individuals with high power and status were collectively oriented and used their power and status for the benefit of the organization. Relatedly, Van der Vegt et al. (2010) found that power asymmetry within teams could hinder team learning, but the effect was contingent on the level of feedback provided: whereas individual-level feedback reinforced the negative effects of power asymmetry on team learning, team-level feedback mitigated those effects.

**Social Networks.** Social networks have been found to facilitate learning and knowledge creation by opening up access to new knowledge sources. As mentioned earlier, Lovejoy and Sinha (2010) showed in a simulation model that the ideation stage of innovation projects can be accelerated when individuals dynamically churn through a large set of conversational partners over time. This process created decentralized networks that facilitated search. The results of empirical studies are consistent with simulation results. For example, Reagans and Zuckerman (2001) found that teams characterized by high demographic heterogeneity had high learning capabilities because the members' networks cut across diverse groups of individuals. Similarly, Tortoriello and Krackhardt (2010) found that ties that span structural holes—ties that bridge otherwise unconnected parts of a network—are helpful for developing new knowledge, especially when individuals who bridge boundaries share common third-party ties.

### 1.5.3 Research Opportunities

We would benefit from learning more about how organizations learn from their own novel or ambiguous experience. Our understanding of how the pace of experience affects organizational learning would also benefit from additional research. For example, one promising research direction is the relationship between the pace of experience and knowledge creation. On the one hand, experience acquired at an uneven rate could hinder knowledge creation more than experience acquired at a steady rate (Argote et al. 1990). On the other hand, such interruption could give organizations opportunities to reflect on their actions and adopt changes to improve performance in the future (Christianson et al. 2009). It would be interesting to understand the conditions under which organizations could benefit from experience being acquired at an uneven rate.

Of the dimensions of the context that have not been investigated much in relation to knowledge creation, the ones that seem most promising to investigate are routines, tools, and slack resources. Although routines are often thought to be a source of inertia, Guo (2019) hypothesized and found that routines can facilitate the creation of knowledge and adaptation to a new task. Although much of the work on tools and organizational learning has focused on the effect of knowledge management systems on search, it would be promising to study the effect of tools such as machine learning on the knowledge creation process. Another interesting direction would be to understand how the distribution of slack resources influences the creation of knowledge. Within organizations, different teams or individuals might have varying levels of access to slack resources held by organizations. Do different organizational members have different perceptions of slack? How would the distribution of slack or the process of negotiating the distribution of slack influence organizational-level knowledge creation?

### 1.6 Knowledge Retention

In addition to the Lockheed case mentioned previously, several other case studies suggested that knowledge acquired through learning might not persist indefinitely (Baloff 1970, Hirsch 1952). Research through the 1980s using the learning curve, however, assumed that learning was cumulative and used cumulative output as the appropriate measure of experience. In this section, we review evidence from studies investigating whether the knowledge acquired from learning is cumulative or whether it depreciates.

Beginning in the 1990s, researchers tested whether learning was cumulative as the classic learning curve implied, or whether the knowledge acquired from learning by doing depreciated. For conceptual clarity, we use the term “depreciation” to refer to the decay of knowledge at the organizational level and reserve the term “forgetting” to describe decay at the individual level. Individual forgetting can contribute to knowledge depreciation at the organizational level, but organizational knowledge depreciation is affected by other factors related to the organizational retention bins discussed previously.

Researchers have investigated the extent to which knowledge depreciates, by estimating a parameter that is a geometric weighting of previous experience. When the parameter is estimated to be less than one, it suggests that knowledge depreciates, because past experience receives less weight than recent experience in predicting current production. Studies have found evidence of depreciation in different organizational contexts, including shipyards (Argote et al. 1990, Kim and Seo 2009, Thompson 2007), automobile assembly plants (Levitt et al. 2013), hotels (Ingram and Baum 1997), and fast-food franchises (Darr et al. 1995). Benkard (2000) provided convincing evidence that depreciation occurred in Lockheed’s production of the L-1011 TriStar and ruled out the explanation that the depreciation was due to changes in the product that made experience from the past obsolete. Comparing depreciation rates across these studies, knowledge depreciates more in contexts with high turnover, such as fast food franchises (Darr et al. 1995), than in contexts with low turnover, such as kibbutzim agriculture (Ingram and Simons 2002). Organizations where considerable knowledge in embedded in technology (Egelman et al. 2017) exhibit little or no depreciation.

These studies advanced understanding by demonstrating that knowledge acquired via learning by doing typically exhibits some depreciation and thus was not cumulative, as the conventional learning curve implied. Incorporating depreciation into forecasts of future productivity results in better estimates. The studies, however, did not determine the cause of depreciation. Studies that take a fine-grained approach to experience or analyze the organizational context provide insights into potential causes of depreciation.

### 1.6.1 Dimensions of Experience

Only a few studies have examined how dimensions of experience affect knowledge depreciation.

**Success vs. Failure Experience**. Analyzing accident experience in U. S. coal mining, Madsen (2009) found that experience from major accidents depreciated at a slower rate than experience from minor accidents. In a study of orbital launches, Madsen and Desai (2010) found that experience from failed launches depreciated less than experience from successful launches.

**Pace of Experience**. Ramdas et al. (2018) took a fine-grained approach to experience by analyzing surgeons' experience with different medical devices used to perform hip replacements. The researchers found evidence of knowledge depreciation in the use of two particular devices, stems and liners, which were difficult to use. For these devices, as the days since the previous usage increased, the duration of the surgery significantly increased, suggesting that the knowledge about how to use the devices depreciated.

### 1.6.2 Organizational Context

Agrawal and Muthulingam (2015) compared the extent to which knowledge embedded in three different repositories in the supply chain of a manufacturing facility depreciated. The researchers found that knowledge embedded in technology exhibited the least depreciation over time, knowledge embedded in routines evidenced intermediate depreciation, and knowledge embedded in individuals exhibited the most depreciation.

**Members.** Studies have examined the effect of knowledge embedded in individuals on knowledge retention by studying the effect of turnover. David and Brachet (2011) compared the effects of member turnover on the effect of skill decay caused by inactivity or task interference on knowledge depreciation. The contribution of member turnover to knowledge depreciation was found to be about twice the effect of skill decay. Studying the turnover of loan officers, Drexler and Schoar (2014) found that the negative effects of turnover were less when turnover was anticipated than when it was not and when the departing member had time and incentives to transfer knowledge to new members.

Examining the interaction between turnover and the organizational context, Rao and Argote (2006) and Ton and Huckman (2008) found that turnover was less harmful in organizations that relied to a great extent on routines and procedures than in organizations less reliant on procedures. The routines buffered the organizations from the effect of membership change. Similarly, Argote et al. (2018) found that the clear coordination logic of centralized communication networks buffered organizations from the effect of turnover: Decentralized networks performed better when membership was stable, whereas centralized networks performed better when turnover occurred. Shaw et al. (2005) found that the departure of members who occupied “structural holes” or bridges between otherwise unconnected individuals was more harmful than the departure of members in dense networks. Kellogg (2011) found significant evidence of knowledge depreciation in a study of learning between firms in contractual relationships, which was attributed to the loss of relationship-specific capital between firms.

**Routines**. Given the important role routines play in storing knowledge in organizations, studies have examined the extent to which organizations follow routines. Analyzing franchise organizations, Knott (2001) found that adherence to routines decreased when units left franchises, which harmed unit performance. In their analysis of pharmaceutical firms, Anand et al. (2012) found that adherence to operational routines decayed over time, especially when a merger occurred. By contrast, inspections from the Food and Drug Administration and acquisitions appeared to halt decay in routines.

**Tools.** Reinforcing the importance of tools as knowledge repositories, research has shown that new members of an organization benefit from the knowledge embedded in tools and routines. Studies of the introduction of a second shift at manufacturing plants found that the new shifts, which were staffed primarily by employees new to the organization, achieved levels of productivity comparable to the existing shifts in record time (Epple et al. 1991, Epple et al. 1996, Levitt et al. 2013). The dramatically faster ramp-ups of productivity on the second relative to the first shifts were due to much of the knowledge acquired by the first shift being embedded in tools and routines that the second shift used.

Interestingly, although IT systems developed before the advent of machine learning stored primarily explicit knowledge, machine learning tools have the potential to embed tacit knowledge that is hard to articulate as well as explicit knowledge (Brynjolfsson and Mitchell 2017). Before recent advances, tacit knowledge that could not be articulated (Polanyi 1966) into a set of rules could not be programmed into a computer. In machine learning, when algorithms are run on training data, the algorithms can capture regularities not even noticed by people. Brynjolfsson and Mitchell (2017) concluded that machine learning algorithms have made it possible to train computer systems to be more accurate than those that are manually programmed for many tasks.

Although the research discussed thus far suggests that knowledge depreciation is bad for the organization because the organization is less productive than it would have been if depreciation had not occurred, several researchers have suggested that depreciation can have positive effects on the organization (Easterby-Smith and Lyles 2011). Using the term “forgetting” to refer to the loss of an organization’s knowledge, de Holan and Phillips (2004) categorized forgetting into accidental and purposeful. Accidental forgetting occurs when an organization does not embed or maintain the knowledge it acquires in organizational memory. By contrast, purposeful forgetting occurs when an organization deliberately fails to embed knowledge or purges knowledge that it deems no longer appropriate or useful. Similar to the benefits of purposeful forgetting, researchers have argued that decreasing memory could weaken inertia and increase an organization’s ability to adapt (Starbuck 1996). Consistent with this argument, simulations have shown that the imperfect recall of information from organizational memory can increase exploration and an organization’s adaptive potential (Jain and Kogut 2014). Jain (2020) concluded that the productivity-improving properties of organizational memory dominate its inertia-producing properties.

### 1.6.3 Research Opportunities

Identifying the conditions under which knowledge depreciation has positive versus negative implications for organizations is an important topic that would benefit from additional research. How to determine what knowledge should be purposefully “forgotten” or purged would also benefit from research. Advocates of forgetting argue that old routines and understandings should be discarded when they are no longer useful or appropriate for a changed environment. Determining when knowledge is no longer useful is a challenging task. Examples exist of knowledge that turned out to be valuable after it was deemed no longer useful. For example, when Steinway decided to put a discontinued piano back into production, it discovered that it did not have records or blueprints of how to make the model (Lenehan 1982).

Very little research has been done on how dimensions of experience affect knowledge retention. Further research is needed to advance our understanding of whether different types of experience depreciate at different rates. For example, heterogeneous task experience has been suggested to foster the development of more high-level, abstract knowledge (Schilling et al. 2003). Would this type of knowledge depreciate at a slower rate than low-level knowledge? Also, would the depreciation rate differ for knowledge gained through exploitation versus exploration? Is the knowledge more likely to be retained when it was acquired before, by, or after doing?

In addition, the topic of contextual influences on knowledge retention merits attention. Research on knowledge retention has focused largely on the role of active contexts (e.g., organizational members, tools), but several interesting questions arise pertaining to the role of latent organizational contexts. For example, how would organizations' absorptive capacity influence the degree of knowledge retention? Because organizations with high absorptive capacity can assimilate valuable information more effectively than organizations with low absorptive capacity (Cohen and Levinthal 1990), would organizations with high absorptive capacity also be more effective in retaining that information than organizations with low absorptive capacity? Another promising topic is the effect of power and status hierarchies on knowledge retention. Would organizations' power or status hierarchies influence the internal process of identifying which knowledge to retain or eliminate from the organization's memory? What about the role of organizational design in knowledge retention?

**1.7 Knowledge Transfer**

Knowledge transfer is the process through which one organizational unit learns from or is affected by the experience of other units (Argote and Ingram 2000). The "unit" could be individuals, groups or the overall organization. Knowledge transfer is also referred to as vicarious learning or knowledge spillover. The latter term is typically used within the field of economics and connotes unintentional spillover, such as might occur within firms in an industry (e.g., see Irwin and Klenow 1994).

Knowledge transfer can occur through a variety of mechanisms, including hiring employees, reverse-engineering products, and acquiring knowledge from suppliers, vendors, consultants, conferences, scientific publications, and patents. Knowledge can transfer through cooperative relationships such as alliances, joint ventures, and consortia. In general, knowledge transfer occurs by moving the knowledge repositories from one organizational unit to another or by modifying the knowledge repositories of the recipient unit (Argote and Ingram 2000). Carlile and Rebentisch (2003) theorized that knowledge transfer occurs through the processes of retrieving knowledge (e.g., searching for knowledge and assessing its usefulness) and transforming the knowledge (e.g., creating shared language) to be used by other units. Further, Myers (2018) proposed a theoretical model of coactive vicarious learning, where a learner and a teacher interact to process experience and derive lessons instead of a one-way process of a learner observing and learning from a teacher.

Researchers have taken several approaches to measure knowledge transfer (Argote and Fahrenkopf 2016). For researchers studying learning curves, just as learning is assessed by the relationship between the experience of a focal unit and the unit's performance, knowledge transfer is assessed by the relationship between the experience of other organizational units and the focal unit's performance. The other organizational units could be units of the same organization as the focal unit (e.g., sister plants producing the same product), units linked to the focal organization through a relationship, such as a franchise or an alliance, or units in firms in the same industry as the focal unit. A statistically significant relationship between the experience of some group of organizations and a focal unit's performance would provide evidence of transfer: the focal unit was affected by the experience of other units. Although the relationship could be negative, it is typically nonexistent or positive, which indicates that the focal unit benefitted from the experience of the other units. Researchers also measure knowledge transfer through survey questions (Szulanski 1996), through changes in routines (Kane et al. 2005), and through patent citations (Alcacer and

Gittelman 2006, Almeida and Kogut 1999, Rosenkopf and Almeida 2003).

The topic of knowledge transfer has received considerable attention in recent years because an organization's ability to successfully transfer knowledge from other organizations or across organizational units can be a source of competitive advantage (Argote and Ingram 2000). Although many studies provided evidence that organizations can transfer knowledge (e.g., Adler 1990, Argote et al. 1990, Salomon and Martin 2008), considerable variance in the extent of knowledge transfer among organizations has been found (Lapré and Van Wassenhove 2001, Szulanski 1996). To understand the source of the observed variation in the effectiveness of knowledge transfer, scholars have examined factors such as the characteristics of knowledge, knowledge senders, knowledge recipients, and organizational contexts, as well as the methods of knowledge transfer such as personnel movement, routine transfer, and so on (for a comprehensive review, see Szulanski and Lee 2020). For example, Zander and Kogut (1995) found that codified knowledge transferred more readily than non-codified knowledge. In this section, we review major findings of how different dimensions of experience and organizational contexts affect knowledge transfer from one organization (or an organizational unit) to another.

### 1.7.1 Dimensions of Experience

**Success vs. Failure Experience**. Several studies have examined whether organizations could learn from other organizations' failures in order to avoid costly learning by themselves. Research has shown that organizations learn from other organizations' failures in various empirical contexts, including railroads (Baum and Dahlin 2007), coal mining (Madsen 2009), and commercial banking industries (Kim and Miner 2007). Recently, several studies have identified conditions that facilitate learning from others' failures, such as the availability of information on others' failures, and motivation and ability to learn from others' failures (see Dahlin et al. 2018). For example, Yang et al. (2015) showed that Japanese firms entering China learned more from the failures of earlier entrants that had prior network ties with the firms than from the failures of earlier entrants without network ties.

Some research has directly compared the effectiveness of learning from others' successes versus failures. Studies generally suggest that organizations learn more effectively from others' failures than from others' successes (KC et al. 2013, Madsen and Desai 2010) for at least two reasons (an exception is Haunschild and Miner 1997, which showed that firms learn from both successes and failures of others). First, organizations typically have easier access to information on others' failures than on their successes, because organizations' failures are often highly publicized, whether by organizations or regulatory agencies (Kim and Miner 2007, Madsen 2009, Madsen and Desai 2010). On the other hand, information on organizations' successes is typically contained internally to sustain their competitive advantage (Katila et al. 2008, Madsen and Desai 2010). Second, organizations are more likely to imitate other organizations' successful strategies blindly without adjusting the strategies to fit their own contexts, whereas other organizations' failures tend to promote deeper search for the fundamental causes of the failures (Sitkin 1992). In a related vein, KC et al. (2013) showed that cardiac surgeons learned from other surgeons' failures because the surgeons attributed others' failures to internal factors such as skills and searched for further learning. On the other hand, the surgeons did not learn from other surgeons' successes because those were attributed to external factors, such as luck, which were not amenable to being imitated. Still, individuals might be able to learn from others' successes if they have easier access to information on others' successes. For example, Song et al. (2018) found that publicly disclosed performance feedback enabled employees to identify whom to learn from and to validate the quality of knowledge held by high performers, and thereby facilitated the transfer of superior practices from high to low performers.

**Ambiguity of Experience.** An organization needs to understand the fundamental factors contributing to the observed outcomes of others in order to learn effectively from the experience of others. As expected, research showed that organizations learned more from others' experiences when the underlying knowledge was less ambiguous and thus easier to understand than when it was ambiguous (King 1999, Szulanski 1996).

**Timing of Experience.** When organizations decide to learn from others' experience (e.g., before or after their own task performance) could influence the effectiveness of knowledge transfer. Although some studies have shown that organizations learned on an ongoing basis from the experience of other units (e.g., Darr et al. 1995), others have shown that organizations learned from other units' experience accumulated up until the organization's founding but not thereafter (Argote et al. 1990, Baum and Ingram 1998). The latter effect is more likely to be found in contexts, such as shipyards and hotels, that require extensive investments in physical infrastructure early on that are not amenable to adaptation on an ongoing basis. Aranda et al. (2017) suggested that organizations tend to learn from other organizations earlier in their own lifecycle than later due to their own lack of direct experience.

**Pace of Experience.** The pace of experience has been suggested to influence knowledge transfer. For example, as noted earlier, Zellmer-Bruhn (2003) found that interruptions, such as a change in technologies or restructuring events, triggered teams to evaluate current routines more mindfully and to learn from others if the current routines were unsatisfactory.

### 1.7.2 Organizational Contexts

**Members.** Because individual members are important channels to transfer both tacit and explicit knowledge (Argote and Ingram 2000), many studies have investigated the effectiveness of transferring knowledge by moving individual members. Although considerable evidence suggests that knowledge transfers to different contexts when individuals move (e.g., Jain 2016, Kolympiris et al. 2019, Rosenkopf and Almeida 2003, Singh and Agrawal 2011), other studies presented a more complex picture. For example, several studies suggested that knowledge held by individuals might not be perfectly transferrable across organizations (Groysberg et al. 2008, Huckman and Pisano 2006). Some portion of individuals' knowledge is organization-specific, such as knowledge of who knows what in organizations and familiarity with organizational resources. Such organization-specific knowledge is not likely to transfer to new organizations. For example, members with specialist experience who are required to coordinate more with other organization members than generalists acquire considerable knowledge that is specific to a particular organization and its members. Specialists have been found to be less likely to transfer their knowledge to new organizations than generalists (Fahrenkopf et al. 2020). Furthermore, groups utilized the knowledge of new members only when the new members were perceived to have high-status (Bunderson et al. 2013), or when the new members provided high-quality knowledge to groups that shared a social identity with them (Kane et al. 2005), or when the new members had expertise in distinct technical domains (Song et al. 2003), or when the previous work experience of the new members was aligned with the structure of recipient groups (Fahrenkopf et al. 2020).

Furthermore, the diversity of organizational members could influence knowledge transfer. Several studies suggested that teams with diverse members (e.g., in terms of organizational tenure, geographic locations) are likely to have access to unique knowledge sources outside of the group and thereby transfer unique knowledge to the group (Cummings 2004, Reagans and Zuckerman 2001).

**Tools.** Tools, including IT systems such as knowledge management systems, online repositories, and social media, can be effective means to transfer knowledge across geographic, temporal, and organizational boundaries (Maslach et al. 2018, Neeley and Leonardi 2018, Wagner et al. 2014). Despite the potential benefits of moving knowledge through tools, studies have identified potential challenges involved in transferring knowledge using IT systems. For example, Hwang et al. (2015) found that in the early phase of using online knowledge communities, individuals shared knowledge only to similar others in terms of hierarchical status and geographical location.

**Organizational Structure.** Several studies found that hierarchical structures hindered the transfer of knowledge. For example, middle managers became more reluctant to pass their subordinates' ideas to superiors when the hierarchy was steeper, because middle managers did not feel that they had control over the outcomes (Reitzig and Maciejovsky 2015). When organizational units were embedded in a centralized hierarchy, the units did not transfer knowledge directly to each other but rather transferred the knowledge indirectly via corporate headquarters, which could be inefficient (Tsai 2002).

Many studies have investigated how an organization's alliance structure (e.g., franchising, shared ownerships, joint ventures, licensing) influences knowledge transfer. Several studies found that knowledge transfers more effectively across units embedded in the same franchise or multiunit chain (Baum and Ingram 1998, Darr et al. 1995). In a related vein, Oxley and Wada (2009) showed that a joint venture with a shared ownership structure, compared to a pure contract-based partnership, facilitated the speed and the extent of knowledge transfer across partners. Interestingly, the joint venture structure was also more effective in preventing unintentional knowledge spillover across partners in domains outside of the alliance agreement. Pierce (2012), however, warned that a shared ownership structure could hinder knowledge transfer more than a pure contract-based structure when the shared ownership creates conflicting incentives among the parties involved. xtending our understanding of when the experience of a common owner is most likely to be valuable, Kalnins and Mayer (2004) found that the locality of the experience mattered. The experience of local units with a common owner was beneficial, whereas the experience of nonlocal units with a common owner was not. Because incentives were constant across co-owned units, incentives were not a viable explanation of the findings. Communication was a viable explanation because communication was denser for co-owned local units than for co-owned nonlocal units. Reinforcing the importance of communication, Kalnins and Chung (2006) found in a different empirical context that knowledge transferred across high-end hotels owned by members of the same ethnic group.

**Incentives.** Several studies have shown that incentives could motivate employees to transfer knowledge. Quigley et al. (2007) showed that dyads with a strong knowledge-sharing norm shared more knowledge with each other when they had a group-based incentive than when they had an individual-based incentive. Similarly, Lee and Puranam (2017) found that a switch from individual pay-for-performance to a fixed salary incentive system facilitated the transfer of knowledge across employees, most likely by making the collective goal salient.

**Physical Space.** Several studies have shown the benefits of colocation on knowledge transfer across units and individuals (e.g., Catalini 2018, Lee 2019). In the context of salespeople in a department store, Chan et al. (2014) showed that individuals learned from peers in the same counters through direct observations and active teaching by their peers. Individuals even learned from peers in physically adjacent competing counters by observing their behaviors. Hatch and Mowery (1998) found that semiconductor plants produced fewer defective products upon adopting a new routine when the manufacturing and routine development facilities were colocated than when they were not colocated. The authors suggested that the colocation of a knowledge sender and a recipient facilitated the transfer of tacit knowledge. Gray et al. (2015) presented similar results in the pharmaceutical industry. In addition, the authors examined whether information and communications technologies (ICTs) could help geographically dispersed units to overcome the barriers of tacit knowledge transfer. They found that ICTs were not as effective as face-to-face communication in transferring tacit knowledge. Several studies showed that it is difficult to transfer knowledge across geographically dispersed teams because members typically have low levels of a shared understanding (Cramton 2001, Gibson and Gibbs 2006). When teams had psychologically safe climates, teams could overcome the communication barriers and transfer knowledge (Gibson and Gibbs 2006).

Despite the potential benefits of colocation on knowledge transfer, some studies also highlighted boundary conditions. For example, in the context of a startup bootcamp, Hasan and Koning (2019) found that individuals were less likely to receive advice from physically proximate others when they already had prior ties to interact with, compared to when individuals did not have such prior ties. In addition, Chatterji et al. (2019) showed that the content of the knowledge exchanged among collocated individuals eventually affected firm performance. By contrast, Darr and Kurtzberg (2000) found that strategic similarity was a more important predictor of knowledge transfer than geographic closeness.

**Organizational Culture and Norms.** Organizational culture and norms have been found to affect the extent of knowledge transfer. Both norms that encourage knowledge holders to share knowledge and norms that guide knowledge recipients' use of the received knowledge (e.g., not passing the received knowledge to others without permission) could influence the transfer of knowledge (Constant et al. 1994, Fauchart and Von Hippel 2008, Merton 1973). For example, Di Stefano et al. (2014) found that Italian chefs were more willing to transfer knowledge to recipients who were expected to conform to the norms of knowledge use than to recipients who were less expected to conform. Examining the role of shared social identity on knowledge transfer, Kane et al. (2005) showed that groups were more willing to adopt high-quality knowledge communicated by new group members when they shared a superordinate social identity than when they did not. Wong (2004) found that groups learned more from individuals outside of the groups when group cohesion was high than low.

In addition, when units within an organization have distinct subcultures, it might be difficult for the units to transfer knowledge across each other due to having different languages or work contexts. Bechky (2003) found that units could overcome this knowledge transfer challenge by paying attention to key differences across units and creating a common ground (e.g., shared language, shared understanding of different work contexts) to communicate with each other.

**Absorptive Capacity.** Research has found that organizations with high absorptive capacity are more adept at identifying and integrating useful external knowledge and therefore learn more effectively from others than organizations with low absorptive capacity (Szulanski 1996, Tsai 2001). Posen and Chen (2013) examined how new entrants, which typically lack absorptive capacity, learned vicariously from incumbent firms. The authors showed that problems encountered during learning-by-doing motivated the new firms to search for knowledge from others and facilitated vicarious learning, despite the lack of absorptive capacity.

**Power and Status.** Power and status differentials among organizational members have been found to influence knowledge transfer. Focusing on social status arising from social ties, Thomas-Hunt et al. (2003) showed that socially isolated members were more likely to share their uniquely held knowledge than socially connected members. Menon et al. (2006) demonstrated that individuals avoided seeking knowledge from rivals within the same organizations due to the threat of losing status and instead sought knowledge from individuals outside their organizations. Raman and Bharadwaj (2012) examined organizational members with power differentials and found that the effectiveness of routine transfer depended on whether the interests of organizations and high-power members were aligned.

**Social Networks.** Research showed that the characteristics of social relationships among parties influence the effectiveness of knowledge transfer across them. Several studies found that high-quality relationships (e.g., strong, cohesive, embedded ties) facilitated the transfer of knowledge between parties and that the benefit was usually greater when transferring tacit, complex, or private knowledge (e.g., Hansen 1999, Ingram and Simons 2002, Levin and Cross 2004, Szulanski 1996, Uzzi and Lancaster 2003). Levin and Cross (2004) found that trust was an underlying mechanism driving the knowledge transfer advantage of strong ties. In a related vein, units or individuals in a competing relationship within an organization were less likely to seek knowledge from and transfer knowledge to each other (Hansen et al. 2005, Menon et al. 2006). Still, Tsai (2002) showed that frequent social interactions among competing organizational units facilitated knowledge transfer across units. He suggested that having social interaction enabled competing units to develop trust and realize opportunities to create synergies.

Many studies examined how the structural characteristics of organizational networks affect knowledge transfer effectiveness. Tsai (2001) found that relative to organizational units in less central positions, a unit occupying a central position in interunit networks produced more innovations by having access to diverse knowledge developed by other units. This effect was strengthened when the unit had a high absorptive capacity. Also, individuals with higher network range perceived transferring knowledge to be easier because they were familiar with being exposed to and communicating diverse knowledge (Reagans and McEvily 2003). Furthermore, several studies suggested that having shared third parties (e.g., mutual contacts of a knowledge source and a knowledge recipient) facilitates knowledge transfer across the source and the recipient by creating cooperative norms and raising the reputation costs of not sharing knowledge (Tortoriello and Krackhardt 2010, Tortoriello et al. 2012). When the ties of a source and recipient do not overlap, these unshared contacts are referred to as unshared third parties. Consistent with the benefits of shared third parties, Reagans et al. (2015) found that unshared third parties reduced the likelihood of the source and the recipient initiating and sustaining knowledge transfer relationships. Further, the negative effect of having unshared parties decreased as the knowledge possessed by the unshared parties became more similar.

### 1.7.3 Research Opportunities

Considerable research has been done about the effect of success versus failure experience on knowledge transfer. More studies are needed to understand the effects of other types of experience on knowledge transfer. We suggest that our understanding of how different types of experience influence the extent of knowledge creation could shed light on the influence of different types of experience on the extent of knowledge transfer. For example, organizations might be able to learn more effectively from the heterogeneous outcome experience of others by inferring valuable lessons via contrasting experience, as organizations did with own heterogeneous outcome experience (Kim et al. 2009). Similarly, as suggested by research on a rare experience's influence on knowledge creation (Madsen 2009, Zollo 2009), the rare experiences of other organizations might either facilitate knowledge transfer by drawing attention to the events or hinder knowledge transfer by triggering superstitious learning, in which inappropriate inferences are drawn about relationships between the actions of other organizations and observed outcomes. Understanding when knowledge transfer is facilitated or impeded by rare experience is an interesting topic for future research.

Studying the effects of different organizational contexts on knowledge transfer is a promising research direction as well. More research has been done on how characteristics of members, organizational design features, absorptive capacity, power and status, and social networks affect knowledge transfer than on the other contextual dimensions. In terms of organizational norms, it would be interesting to see whether norms of knowledge sharing and norms of knowledge use play complementary or substitutable roles in facilitating knowledge transfer within organizations. For example, would it be enough to have appropriate norms of knowledge use (e.g., ensuring that the shared knowledge would not be used against the original knowledge holder) to encourage knowledge transfer? Another interesting direction would be to examine how different active contexts (e.g., members, tools) complement or substitute each other in facilitating knowledge transfer. For example, suggesting a complementary relationship between members and tools, Galbraith (1990) found that knowledge transfer was greater when individuals were moved along with tools than when only tools were moved. In a similar vein, would a routine transfer be more effective if accompanied by personnel transfer? When would it be most beneficial for organizations to rely on members, and when would it be effective to rely on tools to facilitate knowledge transfer?

## 1.8 Future Directions

In each section on learning processes, we have noted areas where there are opportunities for future research on the process. In this section, we discuss future research directions that pertain to the relationships between the different learning processes. We also discuss how new technologies and organizational forms are likely to affect organizational learning. We conclude by discussing methodological developments that have promise for advancing our understanding of organizational learning.

1. A promising question that would benefit from additional research is about the relationship between the processes of organizational learning. Several studies have shown that learning from direct and learning from indirect experience are complements: the more that organizations learn from their own experience,

the more they are able to learn from the experience of other organizations (Bresman 2010). Other studies have shown that the two learning processes are substitutes: organizations who learn a great deal from their own experience do not learn very much from the experience of others (e.g., Wong 2004). Similarly, examining the relationship between knowledge retention and knowledge transfer, Levine and Prietula (2012) found that the two processes were substitutes: greater access to knowledge in organizational memory decreased the benefits of knowledge transfer. Understanding the conditions under which the learning processes complement or substitute for each other is an important topic that would benefit from additional research.

2. Organizational member stability has been found to have different effects on different learning processes. Team member stability has a positive effect on knowledge creation (Reagans et al. 2005) and knowledge retention (e.g., Liang et al. 1995). Membership change, however, has been found to facilitate knowledge transfer (e.g., Choi and Thompson 2005, Kane et al. 2005, Rosenkopf and Almeida 2003, Song et al. 2003). Understanding how to balance membership stability and membership change and the degree of member stability that is most appropriate for different contexts would advance understanding of organizational learning.
3. A topic that has gained attention recently is the role of physical space in organizational learning. The interactions among individuals have been found to be bounded by an organization's physical space, even with the development of information and communication technologies (e.g., Gray et al. 2015). Indeed, organizations' physical designs that limited interactions between individuals have been found to hinder collaborative innovation efforts (e.g., Catalini 2018) or to prevent learning from others (e.g., Lee 2019). Somewhat surprisingly, office designs such as open-space (compared to closed-space) offices have been found to decrease face-to-face interactions and to increase electronic communication among individuals, presumably due to privacy concerns (Bernstein and Turban 2018). Szulanski and Lee (2020) noted that some types of knowledge (e.g., tacit knowledge) can be best transferred through face-to-face interactions, and therefore these new forms of organizational physical space may have substantive effects on learning. In sum, it would be worthwhile to gain a better understanding of the

effects of organizational spatial design on organizational learning.

4. It would also be worthwhile to understand the effects of sharing a social identity on organizational learning. Individuals classify themselves and others into categories based on common characteristics, such as demographic characteristics, organizational affiliations, or national identities (Ashforth and Mael 1989, Hogg and Turner 1985). A shared social identity exists when individuals perceive themselves as belonging to the same group and the group is important to them. This shared identity can exert a powerful influence on what group members think and feel and how they behave (Doosje et al. 1995). For example, individuals who share a social identity perceive each other more positively (Hewstone et al. 2002) and are more willing to cooperate (Tyler and Blader 2000) than individuals who do not share an identity. In the area of organizational learning, evidence exists that sharing a social identity increases the likelihood of knowledge transfer (Kane et al. 2005). Does sharing a social identity affect the interpretation of experience, the search for knowledge, or its retention? Understanding the effects of a shared identity on organizational learning processes is a fruitful area for future research.
5. A promising development in research on organizational learning is understanding how to overcome biases or challenges that occur in organizational learning, such as "superstitious learning," where individuals draw inappropriate inferences from experience (Levitt and March 1988) or the "hot-stove" effect, where individuals undersample alternatives for which the initial experience was negative (Denrell and March 2001). Researchers are investigating the effectiveness of various organizational designs and procedures for counteracting these biases (Puranam and Maciejovsky 2020). For example, Paulus and Kenworthy (2020) discussed how to overcome biases in creating knowledge. Hinsz et al. (2020) presented ways to lessen biases in retaining knowledge. Larson Jr. and Egan (2020) presented procedures for overcoming biases in knowledge transfer. Understanding biases and how to reduce them provides a more unified treatment of the conditions under which experience is a good or bad teacher in organizations and thus would advance our understanding of organizational learning.
6. New forms of organizational structures have been emerging that have implications for organizational learning. For example, hierarchies have become flatter, and self-managed and fluid teams are being

used widely (Bernstein et al. 2016, Puranam 2018, Robertson 2015). What implications do these changes in structural designs of organizations have for organizational learning? Hierarchies have been found to have positive influences on organizational learning in certain conditions (e.g., Bresman and Zellmer-Bruhn 2013, Bunderson and Boumgarden 2010), but have been found to have negative influences on organizational learning in others (e.g., Bresman and Zellmer-Bruhn 2013, Sorenson 2003). Understanding the conditions under which hierarchy facilitates or constrains organizational learning is an important topic that would benefit from additional research.

7. The increase in platforms, especially two-sided ones, has interesting implications for organizational learning. Platforms are business models that create value by facilitating exchanges between suppliers and customers (Zhu and Liu 2018). Examples of two-sided platforms include Amazon.com or Hotels.com. Platforms are an interesting ecology for studying learning, because the organizations on the platform are learning both from their own experience and the experience of other organizations on the platform. Supplier firms on these platforms, such as product manufacturers or hotels, expose and sell their products and services to a mass body of customers through the platform. Customers not only purchase products and services on these platforms, but also often leave feedback and rate supplier organizations. These attributes of platforms have interesting implications for the learning of supplier firms on the platform. Importantly, supplier firms have increased opportunities to vicariously learn from the experience of other firms and adjust their offerings or develop new products and services based on the feedback that others are receiving. In addition, operators of two-sided platforms (e.g., Amazon) can also learn from data that is accumulated on the platform and expand into businesses that they otherwise would not have (e.g., their own brand of clothes or everyday essentials such as vitamins). In other words, the cost associated with searching for new solutions is likely to significantly decrease for the players and the operator of the platform and thus make vicarious learning easier. At the same time, because learning becomes relatively easy on platforms, competition between supplier firms or between supplier firms and the platform operator can increase over time. Accordingly, it would be interesting to examine the dynamics of learning and competitive behavior on these platforms. It would

be interesting to examine the temporal patterns of learning on these platforms, especially related to firms' attempts to prevent external knowledge transfer to competitors in the long run (e.g., Argote and Ingram 2000).

8. Another promising research agenda centers on the relationship between artificial intelligence and human intelligence in organizational learning. What role will machine learning play in organizational learning? What are the conditions under which machine learning is likely to be adopted in organizations? What are the conditions under which results of machine learning will be trusted in organizations? How will information provided by machine-learning tools and information provided by members be integrated in the process of organizational learning?
9. Understanding the role of "big data" in organizational learning also merits attention. From the search of sites by individuals to locations of phone calls, large amounts of data are currently available to organizations. Will greater availability of data enable organizational learning? As Ocasio et al. (2020) note, information has to be attended to in order to have an effect, so factors affecting attention come into play in selecting and interpreting data. For high-level strategic decisions in organizations, there is often a paucity of data rather than an abundance of it (e.g., March et al. 1991). What data will organization members attend to? How will information based on big data be combined with more qualitative judgments?
10. Career trajectories have changed for individuals, where individuals now actively search for better jobs and engage in voluntary turnover instead of staying in a single organization throughout their entire careers (e.g., Cappelli 1999, Direnzo and Greenhaus 2011). Due to this phenomenon, possessing valuable and exclusive knowledge has become increasingly important for organizational members. What implications does this have for knowledge creation, transfer, and retention in organizations? Will individuals with more valuable knowledge be less willing to apply their knowledge or share their knowledge with others in an organization? Will any of an individual's knowledge be retained by the organization if the individual were to leave? How would this phenomenon affect organizations' motivation to invest in firm-specific human capital (e.g., Becker 1962) and subsequent knowledge

creation processes in organizations?

11. Another interesting phenomenon related to organizational learning is that organizational knowledge that creates competitive advantage might become obsolete quicker than before, due to fast-changing environments. What implications does this have for organizational learning? For example, when does prior experience facilitate organizational learning (e.g., Cohen and Levinthal 1990), and when does it act as inertia and hinder organizational learning? What kind of knowledge should be retained, and what knowledge should be purged to sustain competitive advantage? Researchers have argued that knowledge depreciation or "organizational forgetting" can reduce inertia and enable adaptation (Jain 2020) and improvisation (Miner and O'Toole 2020) in organizations. Understanding the conditions under which knowledge depreciation is a source of competitive advantage is an important agenda for future research.
12. How should organizations think about hiring or firing employees in these fast-changing environments? On the one hand, valuable prior knowledge is embedded in employees. On the other hand, new knowledge stock cannot be easily acquired in a short period of time by the same individuals (e.g., Dierickx and Cool 1989). When is it better to hire individuals who have the desired knowledge, and when is it better to develop the knowledge internally in current employees? In sum, more research on organizational learning in quickly changing environments is needed.
13. On the methodological side, developments in neuroscience have the potential to advance our understanding of organizational learning (Senior et al. 2011). Using these tools has led to advances in our understanding of individual learning. For example, Laureiro-Martínez et al. (2015) used functional magnetic resonance imaging, fMRI, to study the exploitation versus exploration decisions of individuals. Because individuals are the mechanism through which much of organizational learning occurs, these studies have implications for organizational learning. Currently, studies using functional magnetic resonance imaging typically confine one individual inside an fMRI machine and ask him or her to respond to stimuli presented on a screen. Shamay-Tsoory and Mendelsohn (2019) enumerated the limitations of tools such as fMRI for studying social cognition and memory: individual participants

are not able to act on or influence the environment; participants' movements are limited; and participants' cognitive abilities are assessed on tasks that do not capture the richness of real-life experience. These features would also limit our understanding of organizational learning. To address them, Shamay-Tsoory and Mendelsohn (2019) have advocated using portable technology, such as portable EEGs (electroencephalography) and functional near-infrared spectroscopy (fNIRs), to study behavior. Portable neuroscience tools have been used to study group learning (see Håkonsson et al. 2016). Their development holds promise for understanding the processes of organizational learning.

14. Another fruitful trend is using laboratory or field experiments to advance the understanding of organizational learning. Laboratory or field experiments have the advantage of enabling the establishment of causality and permitting the investigation of mechanisms' underlying effects. Examples of studies that have used laboratory experiments to study the topic of organizational learning include Cohen and Bacdayan (1994), Fang (2012), Kane et al. (2005), Liang et al. (1995), and Schilling et al. (2003). Field experiments on the topic have been relatively scant but are growing in number. Some examples include Bernstein (2012), Di Stefano et al. (2014), and Song et al. (2018). Compared to field experiments, laboratory experiments allow more control over extraneous variables. However, because of the controlled setting, results from a laboratory experiment are typically lower in external validity than field experiments. Field experiments, on the contrary, are conducted in the real-life environments of participants; thus, the findings derived from them usually have high external validity. The use of laboratory and field experiments in conjunction with empirical studies using archival data, qualitative studies, or simulations would be a powerful combination that holds promise for advancing the understanding of organizational learning.

15. We hope that the trend of investigating the mechanism through which learning occurs continues. Learning is determined by the opportunity to learn, the motivation to learn, and the ability to learn (Argote et al. 2003, Dahlin et al. 2018). It would be useful to use this framework to understand better what promotes and hinders organizational learning in general. For example, opportunities to learn could depend on social networks (e.g., Lovejoy and Sinha 2010, Reagans and McEvily 2003). The motivation

to learn could depend on incentives (e.g., Clark et al. 2018, Lee and Meyer-Doyle 2017, Lee and Puranam 2017). The ability to learn could depend on prior experience (e.g., Cohen and Levinthal 1990) and training (see Bell et al. 2017, for a review). In sum, a deeper understanding of the mechanisms through which learning is promoted or hindered would be valuable.

### 1.9 Conclusion

Organizational learning is a vibrant research area that has attracted researchers from a variety of disciplines. From understanding the micro-foundations of organizational learning to determining its implications for the strategic behavior of firms, researchers are advancing knowledge. In this article, we aimed to take stock of what is known about organizational learning, identify important gaps in our knowledge, and suggest future directions that are likely to lead to greater understanding. These future directions include discerning how important technological and organizational developments, such as machine learning and new organizational forms, affect organizational learning. We hope that our work stimulates additional research on organizational learning. Not only will further research on organizational learning advance theory, but it also has the potential to advance practice. Learning is a key contributor to the performance of organizations and a major source of their competitive advantage.

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# CHAPTER 2. GIVING UP LEARNING FROM FAILURES? AN EXAMINATION OF LEARNING FROM ONE'S OWN FAILURES IN THE CONTEXT OF HEART SURGEONS

**Abstract**
We reassess existing theories on individual failure learning and propose an inverted-U-shaped relationship between an individual's own accumulated failures and learning, based on a theoretical framework that jointly considers the opportunity, motivation, and ability to learn. Using data on 307 California-based cardiothoracic surgeons who performed coronary artery bypass graft surgeries in 133 hospitals between 2003 and 2018, we find strong evidence of individuals "giving up" on learning from their own failures after a certain threshold. We also find that this threshold is higher for surgeons who received elite education, had certified expertise, and specialized in patient care. This paper aims to shed new light on the relationship between individuals' own failure experience and individual learning and advance our understanding of the microfoundations of organizational learning.

## 2.1 Introduction

Individual learning is an important microfoundation of organizational learning (Kim 1998, Argote 2013, Argote et al. 2021), and individuals' own failure experiences have been highlighted as important sources of individual learning (Ellis and Davidi 2005, Wilhelm et al. 2019). Failures have been defined as undesired performance outcomes that deviate from expected organizational goals (Dahlin et al. 2018). In line with the experiential learning literature (Levitt and March 1988, Sitkin 1992, Argote and Miron-Spektor 2011, Kolb 2015), researchers have often viewed failure cases as units of experience and theorized that accumulated failures will lead to learning and improved performance for individuals, and ultimately for organizations (Desai 2015, Dahlin et al. 2018, Avgerinos et al. 2020). A close examination of the literature on this topic, however, reveals that theories and findings on individual learning from one's own failures are inconsistent.

On the one hand, some research has found that individuals effectively learn from their own failures (e.g., Ellis and Davidi 2005, Wilhelm et al. 2019, Avgerinos et al. 2020). These findings are consistent with theories that suggest that failures facilitate cognitive processes—such as seeking causal explanations—that lead to learning (Wong and Weiner 1981, Hastie 1984, Louis and Sutton 1991, Taylor 1991, Ellis and Davidi 2005), and subsequently trigger actions of updating existing knowledge to avoid repeating similar failures in the future (Zakay et al. 2004, Ellis et al. 2006). On the other hand, some studies have found that individuals do *not* effectively learn from their own failures or even perform worse after experiencing them

(KC et al. 2013, Deichmann and Ende 2014, Eggers and Song 2015, Eskreis-Winkler and Fishbach 2019). The dominant theories in this stream of literature suggest that this is due to failures evoking negative emotions such as shame, embarrassment, helplessness, fear, burnout, and loss of self-esteem (Staw et al. 1981, Seo et al. 2004, Cannon and Edmondson 2005, Shepherd and Cardon 2009, Zhao 2011, Roulet 2020, Vogus et al. 2020, Dahl and Werr 2021) or triggering attribution biases that lead to individuals disassociating themselves from their own failures (Jordan and Audia 2012, KC et al. 2013).

Altogether, studies have revealed starkly contrasting findings and have provided different but compelling theories to explain these results. From an overarching theoretical standpoint, however, it is unlikely that failures trigger only processes conducive for learning and not those that prevent learning, and vice versa. Rather, these processes are likely to coexist but vary in their relative strengths, where one dominates the other under certain conditions. Understanding this dynamic process would be crucial to better predicting how a particular failure would affect learning. This understanding becomes especially important in contexts where failures occur repeatedly over time, as is the case for many organizations such as research laboratories (Shepherd et al. 2011, Khanna et al. 2016), manufacturing firms (Haunschild and Rhee 2004, Maslach 2016), and hospitals (KC et al. 2013, Desai 2015, Lee et al. 2021).

In this paper, we synthesize existing theoretical viewpoints on the effect of individuals' own failures on individual learning and propose a *curvilinear* main relationship between them. In specific, building on a theoretical framework on individuals' own failure learning that jointly considers the opportunity, motivation, and ability to learn from these failures (Dahlin et al. 2018), we first propose that there will be an inverted-U relationship between a person's own accumulated failures and individual learning due to opposing effects of the opportunity and motivation to learn. Then, we propose that this relationship will be moderated by an individual's (perceived) ability to learn. In sum, we predict that as individuals experience more of their own failures, there will be a point at which they *give up* or cease learning from them because they lose the motivation to do so. Although we expect individuals' motivation to learn from their own failures to eventually fall below this threshold as they accumulate more failures, we argue that individuals with more positive beliefs about their abilities to understand causes of their failures and to find/implement solutions to prevent them will retain their motivation to learn longer (e.g., Bandura 1977, 1982, Ajzen 1991), and thus persist in learning from their own failures longer than their counterparts.

We test our hypotheses using data on 307 California-based cardiothoracic surgeons who performed isolated coronary artery bypass graft (CABG) surgeries in 133 hospitals between 2003 and 2018. In this context, failures are patient deaths resulting from CABG surgeries, and individual learning is captured through improvements in surgeons' surgery performance after such experiences. Our results confirmed the inverted-U-shaped relationship between individuals' own accumulated failures and individual learning; surgeons' performance increased as a function of their accumulated failures up to a point but then decreased afterward. We also found that this inflection point came later for surgeons who were hypothesized to have higher (perceived) abilities to learn—namely those with elite training, with certified expertise, and specialized in patient care.

Our study makes important contributions to the learning literature. First, by developing and testing a revised theoretical model on individual failure learning, we contribute to the literature on individual failure learning in organizations (Shepherd et al. 2011, KC et al. 2013, Wilhelm et al. 2019, Avgerinos et al. 2020, Lapré and Cravey 2022). Particularly, we theorize and show a novel curvilinear main relationship between individuals' own accumulated failures and learning. Our results suggest that accumulating one's own failures simultaneously triggers both forces that presumably increases the opportunity to learn and decreases the motivation to learn; thus, learning outcomes will depend on which force is dominating. Second, our study also has important implications for the literature on organizational learning (Argote and Miron-Spektor 2011, Argote 2013, Argote et al. 2021). We find that even within the same organization, there is individual-level heterogeneity in the amount of one's own failure learning depending on an individual's qualifications or past experiences. Because organizational learning depends on levels of learning achieved by individuals, our study highlights the need for greater attention to the antecedents of such individual-level heterogeneity. Finally, our study has implications for organization design and strategic human capital management, particularly in the areas of hiring and training. Our results suggest that organizations can improve performance by hiring employees that are more resilient to repeated failures or training them to become so. Overall, the goal of our paper is to shed new light on the relationship between individuals' own failures and learning and to open up exciting opportunities for research on the microfoundations of organizational learning.

**2.2 Theory and Hypotheses**

Failure learning has been defined as "the process by which individuals, groups, or organizations identify error or failure events, analyze such events to find their causes, and search for and implement solutions to prevent similar errors or failures in the future" (Dahlin et al. 2018, p. 254). Essentially, failure learning is a type of experiential learning that involves individuals, groups, or organizations learning from failure experiences. Although some experiential learning may occur somewhat unconsciously or automatically (Dutton and Thomas 1984, Lapré et al. 2000), failure learning has been argued to require analytical learning—a process that involves active decision making that uses information about a prior experience to reshape future routines (Reason 1990, Dahlin et al. 2018). In this regard, it is important to understand how individuals—the core decision makers in organizations—learn from their failures.

Intriguingly, the literature on individual learning from failure has shown contrasting results. On the one hand, some studies have found that individuals learn from their own failures. For example, in the context of Israeli soldiers, Ellis and Davidi (2005) found that individuals developed rich mental models of causal relationships between task inputs and outputs after their own failures. Similarly, Avgerinos et al. (2020) found that cardiothoracic surgeons went through a process of "sensemaking" after experiencing failures, which improved their performance over time. These findings parallel theories that argue that failures generate valuable information for learning and trigger cognitive processes or actions that help individuals update existing knowledge structures to improve performance (Wong and Weiner 1981, Hastie 1984, Louis and Sutton 1991, Taylor 1991, Zakay et al. 2004, Ellis and Davidi 2005, Ellis et al. 2006).

On the other hand, researchers have found that individuals do not effectively learn from their own failures or even perform worse after experiencing them. For example, in a lab experiment, Eskreis-Winkler and Fishbach (2019) found that individuals could not learn from failure feedback because they "tuned out" from learning to protect their egos (see also Roulet 2020). KC et al. (2013) also found that cardiothoracic surgeons did not learn and even performed worse after their own surgical failures due to self-serving attributions. Similarly, Eggers and Song (2015) found that serial entrepreneurs whose ventures failed tended to blame the external environment and moved on to creating a subsequent venture in a different industry instead of trying to learn from their failures. Altogether, these findings are consistent with the theories suggesting that failures trigger negative emotions (Staw et al. 1981, Seo et al. 2004, Cannon and Edmondson 2005, Shepherd and Cardon 2009, Zhao 2011, Vogus et al. 2020) or attribution biases (Jordan and Audia 2012, KC et al. 2013), which lead individuals to disengage from learning from their own failures.

Though these prior results provide valuable insights independently, they collectively suggest that existing theories and findings are incomplete. Notably, recent studies have started to examine the boundary conditions under which individuals are more likely to learn from their own failures (e.g., Shepherd et al. 2011, Wilhelm et al. 2019, Avgerinos et al. 2020, Lapré and Cravey 2022). For example, Avgerinos et al. (2020) found that individuals may not learn from their recent failures because it takes time to make sense of them. Shepherd et al. (2011) theorized that learning from one's own failures depends on individuals' ability to cope with failures and on organizational culture of failure tolerance. Wilhelm et al. (2019) found that employees are more likely to learn from their failures if they work in psychologically safe teams with well-developed transactive memory systems. Finally, Lapré and Cravey (2022) suggested that failure learning depends on the frequency of failures and whether an objective root-cause-analysis can be conducted on failures.

Overall, prior studies have advanced our understanding of individual failure learning; however, at least three important limitations remain. First, a large portion of studies on individual failure learning examine the effect of only a *single* failure on learning (Ellis et al. 2006, Shepherd et al. 2011, Wilhelm et al. 2019). Such research design precludes the opportunity to examine the effect of a failure in different ranges (low/moderate/high) of accumulated failures. Second, these studies often rely on theoretical assumptions that individuals' own failures affect learning only either positively or negatively (Zakay et al. 2004, Ellis and Davidi 2005, KC et al. 2013, Lapré and Cravey 2022). This precludes the possibility that the positive and negative effects of failures on learning interact with each other to form other intricate patterns of learning. Third, prior studies lack theorization and evidence about when and why failure learning rates vary for different individuals (with exceptions such as Shepherd et al. 2011). This is a big gap in the literature, because organizations are comprised of individuals with different characteristics, which create heterogeneity in their learning patterns (Reagans et al. 2005, Lee 2019). Altogether, addressing these limitations will enable better understanding of the effects of individuals' own failures on learning. In the next section, we synthesize the existing literature and develop a revised theory for the relationship between individuals' own accumulated failures and learning, which we test using data on cardiothoracic surgeons who experience failures in the form of patient deaths.

### 2.2.1 Individual learning from failures: An interplay of the opportunity, motivation, and ability

In a recent review of the literature on learning from failures, Dahlin et al. (2018) advised researchers to develop theoretically sounder frameworks by being mindful of the mechanisms that affect learning from failures. Especially, they suggested that an interplay of three factors—the *opportunity*, *motivation*, and *ability to learn*—will determine the effectiveness of one's learning from failures. The *opportunity to learn* is the scope and amount of information available for an individual to learn from failures; the *motivation to learn* refers to an individual's desire to put in efforts to learn from past failures and prevent future failures; the *ability to learn* is an individual's capacity to understand causes of failures and to find/implement solutions to prevent future failures.

Building on Dahlin and colleagues' framework, we theorize in the following sections that the main relationship between an individual's own accumulated failures and learning will be driven by an individual's opportunity and motivation to learn, and that this relationship will be moderated by their (perceived) ability to learn, particularly through its effect on their motivation to learn.

### 2.2.2 Accumulation of Failures and the Opportunity and Motivation to Learn

We expect one's opportunity and motivation to learn to work in parallel but in opposite directions as individuals accumulate failures. As aforementioned, the opportunity to learn from failures refers to the scope and amount of information that allows individuals to learn from failures (Dahlin et al. 2018). In many organizational contexts, individuals often experience comparable failures repeatedly (e.g., Lapré and

Cravey 2022). For example, in our study's empirical context, surgeons repeatedly experience patient deaths from surgeries. Although the types of failures experienced by these individuals are similar, the details of each failure differ. Thus, each new failure offers unique knowledge that can synergistically modify and extend the existing knowledge of these individuals, opening up opportunities for continuously improving task performance.

Additional failures will provide useful learning opportunities especially in complex task environments of modern organizations where recent experience can continue to provide novel information. In our empirical context, surgeons constantly face new surgery techniques, changes in coordination patterns with other hospital members, advancements in hospital technologies, and increasing heterogeneity in patient conditions. In these contexts, failures occurring at different points in time can increase individuals' quantity of knowledge by providing knowledge that they lacked or increase the quality of knowledge by updating incomplete or incorrect knowledge (Lai 2021). In this regard, we expect that the opportunities to learn will increase as failures accumulate.

At the same time, and in contrast, we expect additional units of failure experience to decrease individuals' *motivation to learn* from their own failures. Earlier, we defined the motivation to learn as the desire to put in efforts to learn from failures and to improve subsequent performance. Prior literature has suggested that failures are important motivators for drawing lessons from experiences (Weiner 1985, Sitkin 1992, Ellis and Davidi 2005), and that negative outcomes will trigger search for alternative solutions (Sitkin 1992, Weiner 2000, Zakay et al. 2004). Thus, when individuals initially face failures in their tasks, we expect them to be highly motivated to analyze, understand, and draw lessons from them to improve subsequent performance.

However, this high motivation to learn from their own failures is likely to decrease as failures accumulate. Prior literature has found that failures, especially repeated failures, dampen the motivation to learn, due to negative emotions triggered by failures (Shepherd et al. 2013). In specific, individuals involved in failures experienced feelings of embarrassment, fear, frustration, pain, anxiety, disappointment, depression, and loss of self-esteem (Edmondson 2004, Shepherd et al. 2011, Roulet 2020, Dahl and Werr

2021). High levels of these emotions will impair motivation to learn from their own failures (Seo et al. 2004, Zhao 2011); thus, we expect the motivation to learn to decrease as individuals' experience more failures.[1] In addition, repeated failures can trigger attribution biases, which can also reduce the motivation to learn from one's own failures. For example, KC et al. (2013) found that cardiac surgeons learned from others' repeated failures but not from their own. The authors explain that this is due to individuals attributing others' failures to controllable factors such as effort and their own failures to uncontrollable factors such as bad luck (Weiner 1974, 2000). When a failure is perceived as uncontrollable, the motivation to learn from it will be reduced (Bandura 1977, Lapré and Cravey 2022). Attribution bias is also related to individuals feeling threats to their self-image when they fail (Jordan and Audia 2012, Eskreis-Winkler and Fishbach 2019, Roulet 2020). To preserve a positive self-image, when individuals experience repeated failures, they tend to engage in self-enhancing behaviors such as ignoring failures and taking on lower performance standards (Audia and Brion 2007, Jordan and Audia 2012, Eskreis-Winkler and Fishbach 2019). This reduces the motivation to learn from their own failures. Altogether, we expect that individuals' motivation to learn will be high when the level of their own accumulated failures is low and will decrease as more failures occur, due to the growing intensity of negative emotions and attribution biases.

So far, we have argued that the opportunity to learn will increase but the motivation to learn will decrease as individuals accumulate failures. We posit that these two latent mechanisms will interact to form an inverted-U-shaped relationship between individuals' own accumulated failures and learning. As discussed earlier, failure learning requires analytical learning (Reason 1990, Dahlin et al. 2018). Hence, to effectively learn from their own failures, individuals will need sufficient levels of both the opportunity and motivation to learn.[2] At low levels of individuals' own accumulated failures, the motivation to learn will be high, but the opportunity to learn will be low because individuals would not have gathered enough

[1] Alternatively, individuals may become more desperate to learn as they fail more. However, prior literature suggests that in such cases, individuals will rather turn their attention to *others'* failures to learn vicariously (Baum & Dahlin, 2007). This is consistent with our prediction that accumulating one's own failures leads to less motivation to learn from such failures. However, we do not find increased vicarious learning in those situations in our context.
[2] In other words, we are theorizing a multiplicative relationship (i.e., interaction) rather than an additive relationship because no learning will occur if either the opportunity or the motivation equals 0 (Haans et al., 2016).

information about the different causes of failures. Thus, despite high motivation, we expect an individual's learning performance to be relatively low in this range of their own accumulated failures. However, as more information is acquired through accumulating failures, the opportunity to learn will increase. Although the motivation to learn may not be as high as initial periods due to the negative emotions and attribution bias triggered by the increasing number of failures, we still expect individuals to have sufficiently high motivation to learn during this period, especially if the focal task in hand is important (e.g., Zhao 2011). Thus, we expect individuals' learning to be highest at moderate levels of accumulated failures. However, once the number of accumulated failures surpasses a certain point, we argue that individuals' motivation to learn from their own failures will be impaired by the overwhelming effect of negative emotions and attribution biases. This will result in individuals *giving up* on learning from their own failures. Although this cessation of learning could merely lead to performance stagnation, in fact, KC et al. (2013) showed that the lack of learning leads to *decreasing* individual task performance over time. This is because individuals are likely to continue behaving in ways that led to the failure and not modify or extend their existing knowledge although the task environment around them is evolving (e.g., Staw 1981, KC et al. 2013). Consistent with these arguments, we expect that individuals' learning performance will deteriorate at high levels of accumulated failures. Figure 2.1 summarizes these arguments.

- Figure 2.1 about here -

Taken together, we hypothesize an inverted-U-shaped relationship between individuals' own accumulated failures and learning:

**Hypothesis 1 (H1)**. *There will be an inverted-U-shaped relationship between an individual's own accumulated failures and learning, such that an individual's performance will increase as a function of their own accumulated failures up to a point but will decrease once that point is passed.*

### 2.2.3 The Moderating Effect of Individuals' (Perceived) Ability to Learn

So far, we have argued that the main relationship between individuals' own accumulated failures and learning would form an inverted-U shape because of increasing opportunities to learn and decreasing motivation to learn as failures accumulate. Although we expect individuals to eventually reach a point at which they lack the motivation to learn (Zhao 2011), some individuals may reach that point later (i.e., at a higher level of their own accumulated failures) than others.

We posit that individuals with higher *(perceived) abilities to learn*—those who regard themselves to be better than others at understanding causes of their own failures and finding and implementing solutions to prevent them in the future—will reach that point later than their counterparts. This is because these individuals will have higher motivation to learn and will be less susceptible to negative emotions and attribution biases caused by repeated failures. We build our arguments off the concept of *self-efficacy*, which is concerned with "judgements of how well one can execute courses of action required to deal with prospective situations (Bandura 1982, p.122)." Because individuals are more likely to put in effort when they believe "I can do this" (Bandura 1977), the perceived ability to learn will be an important driver of an individual's persistence and motivation to learn (Zimmerman 2000, Cook and Artino Jr 2016). Importantly, our theory does not require individuals to actually have high ability to learn; rather, their mere beliefs that they are competent in learning from their own failures are sufficient for our proposed moderation effect, as such beliefs will positively affect their motivation to learn and trigger more persistent learning behaviors (see also Ajzen's (1991) concept of perceived behavioral control in his theory of planned behavior). In the next paragraphs, we elaborate on why higher (perceived) ability to learn will positively moderate the relationship between individuals' own accumulated failures and learning.

To begin with, individuals with higher (perceived) ability to learn will have higher motivation to learn than their counterparts. Especially, the literature on self-efficacy has suggested that individuals who have stronger beliefs in their ability to execute a given task are likely to pursue higher goals. For example, Zimmerman et al. (1992) found that students with high self-efficacy set higher academic goals than those with low self-efficacy. Importantly, the literature on goal-setting theory has suggested that pursuing higher (harder) goals will increase motivation, as long as those goals are not impossible to achieve (Locke and Latham 1990, 2002, 2006). This implies that individuals with higher (perceived) ability to learn will start off with a larger 'stock' of motivation to learn from their own failures, which will be depleted later than those with lower (perceived) ability as their failures accumulate.

Second, we expect the motivation of individuals with higher (perceived) ability to learn to be less attenuated by the negative emotions triggered by their own failures than those of individuals with lower (perceived) ability to learn. Especially, error management research has shown that individuals with high self-efficacy have less negative emotional reactions to errors (Rybowiak et al. 1999), exhibiting the attitude of "no worries, can do" (Seckler et al. 2021). Prior studies have also suggested that individuals will persist through failures, despite feeling negative emotions, particularly when they feel that the causes of failures are fixable and under control (Bandura 1997, Zimmerman and Schunk 2006, Cook and Artino Jr 2016, Lapré and Cravey 2022). For example, in the context of Formula 1 racing, Lapré and Cravey (2022) found that despite the frustration and disapointment car racers feel when they cannot complete a race due to a car failure, they learn from these failures because they and their teams believe they are capable of objectively analyzing the root cause of the problem and fixing the car for the next race.

Finally, we argue that individuals with high (perceived) ability to learn would be less susceptible to attribution biases after their own failures. We discussed above that individuals with stronger beliefs in their abilities to execute a task will pursue higher goals. The education literature has shown that individuals who set higher goals are less likely to attribute their worst marks to uncontrollable causes, such as teachers' skills, than their counterparts (Walkey et al. 2013). This implies that individuals with high (perceived) ability to learn will be more likely to attribute their own failures to controllable factors, such as their own effort, than their counterparts (Weiner 1985). Importantly, attribution theory suggests that individuals will be more motivated to learn from their own failures when they attribute them to internal and controllable factors (KC et al. 2013, Lapré and Cravey 2022, Park et al. 2022).

In sum, we expect individuals with higher (perceived) ability to learn to persist longer in learning from their own failures than their counterparts, due to their relatively higher motivation to learn from them. As aforementioned, because each failure provides additional opportunities to learn, those who persist longer in actively learning from failures will have a higher chance of obtaining knowledge that will further improve their performance for that time being. Therefore, we predict that the inverted-U-shaped relationship between their own accumulated failures and learning hypothesized in H1 will shift to the right for these individuals, as depicted in Figure 2.2.[3]

- Figure 2.2 about here -

In our context of cardiothoracic surgeons, we expect at least three types of surgeons to have higher (perceived) ability to learn than other surgeons: (1) those with elite training in cardiothoracic surgery, (2) those with certified expertise in surgery, and (3) those who specialized in patient care instead of other task responsibilities (e.g., teaching). This conceptualization is consistent with that of Greenwood et al. (2019) who theorized in the context of cardiologists that individuals who received elite education, obtained board certification, and accumulated high levels of task experience have higher expertise than their counterparts. As a result of such expertise, these individuals tend to be more confident in their ability to understand the causes of their own failures and find appropriate solutions to prevent future failures. Accordingly, we expect these three types of surgeons to have higher (perceived) ability to learn than other surgeons. Ultimately, we predict that these individuals will cease learning from their own failures at a significantly later point (i.e., at higher levels of accumulated failures) than those who perceive themselves to have lower ability to learn from their failures. Hence, we hypothesize:

> **Hypothesis 2 (H2)**. *The inflection point of the inverted-U-shaped relationship hypothesized in Hypothesis 1 will form at higher levels of individuals' own accumulated failures for individuals* ***a)*** *with elite education in the focal task,* ***b)*** *with certified expertise in the focal task, and* ***c)*** *who specialize in the focal task, compared to their counterparts.*

## 2.3 Method

### 2.3.1 Empirical Context, Data, and Sample

We test our hypotheses using comprehensive biannual data on cardiothoracic surgeons performing isolated CABG surgeries in California. California Department of Health Care Access and Information (HCAI) reports that coronary artery disease is the most frequent cause of non-maternal adult admissions to Californian hospitals, and CABG surgeries are the most adopted surgical procedure for the disease. Our context is favorable for examining surgeons' learning from their own failures for several reasons. First, we

[3] Please see Haans et al. (2016) for moderation of U-shaped relationships. Moderation could result from either a slope change or an intercept change in one of the latent processes underlying the U-shaped relationship. In our study, we are proposing that the moderation mainly occurs through the intercept change in the motivation to learn from failures.

can objectively measure failures and learning using established measures in the literature (Huckman and Pisano 2006, KC et al. 2013, Desai 2015). Second, we can examine how surgeons respond to different levels of their own accumulated failures, because surgeons experience multiple patient deaths over time. Third, we have fine-grained microdata on each surgeon's backgrounds (e.g., education, certification, and specialization), allowing us to capture how different types of surgeons learn differently from their own failures.

We merged ten different data sources to build a panel data to test our hypotheses. First, we created the main data of surgeons who performed isolated CABG surgeries in California and their surgery performance using the available reports by the HCAI during 2003-2018. As it was mandatory for hospitals to submit this data, the data represent the entire population of 493 surgeons who performed isolated CABG surgeries in California from 2003 to 2018 (4,446 surgeon-hospital-period observations). The data provided information on surgeons' names, affiliated hospitals, number of isolated CABG surgeries performed, observed number of patient deaths, expected number of patient deaths based on patients' risks, and patient risk-adjusted mortality rates. Surgeons confirmed the data accuracy before each report's publication.

After creating lagged variables, our final sample included 2,808 observations of 307 surgeons who performed 177,574 isolated CABG surgeries and experienced 4,216 failures in 133 hospitals from 2003 to 2018.

Next, we collected data to construct moderators and control variables. To test H2a (elite education), we collected data on each surgeon's cardiothoracic training hospitals. This data was hand collected from multiple websites, including the Medical Board of California, hospital websites, Google, LinkedIn, Healthgrades, Doximity, U.S. News & World Report, the American College of Surgeons website, and CTSNet (the largest web community for cardiothoracic surgeons). Importantly, we used clear identifiers such as surgeon's name, location of practice (California), specialty, medical school information, and license number to verify each match. We then identified elite (top 30) cardiothoracic training hospitals using the U.S. News & World Report's Best Hospitals for Cardiology and Heart Surgery list. This ranking was determined based on objective and quantifiable data on hospitals' patient care quality (i.e., surgery performance, patient satisfaction, etc.). Our interviewees acknowledged that training from these institutions would lead to higher (perceived) ability to learn from failures.

To test H2b (certified expertise), we collected data on surgeons' Fellow of the American College of Surgeons (FACS) status through the websites listed above. FACS designation was given only to surgeons who met exceptional qualification standards. Specifically, surgeons were evaluated rigorously based on factors such as board certification, reference letters from current fellows, and surgery performance in recent months. The surgeons we interviewed corroborated that this status represents stronger confidence in improving surgery performance.

To test H2c (specialization), we retrieved detailed surveys filled out by surgeons, from the Medical Board of California website, which included information on how each surgeon allocated time across different tasks (e.g., patient care, research, etc.). Just as in universities where some faculty focus on research (e.g., research-track faculty) and some on teaching (e.g., teaching-track faculty), there are surgeons who specialize in patient care (surgeries) over other tasks. Naturally, these surgeons tend to be better at understanding surgical procedures and causes of failures, making them more willing to and confident about learning from their failures.

Finally, we used the HCAI's annual hospital utilization reports and the American Hospital Association's annual surveys to create control variables. We also held 30-minutes to 1-hour long semi-structured interviews with 25 surgeons and physicians affiliated with 17 medical centers to better understand our empirical context and corroborate the validity of our measures and findings.

**2.3.2 Measures**

**Dependent Variable.** Following prior literature, we measured *learning from failures* as an increase in a surgeon's performance in the period after experiencing patient deaths (KC et al. 2013, Desai 2015). Patient risk-adjusted mortality rate is one of the most commonly used surgical performance measures (Huckman and Pisano 2006, KC et al. 2013). We captured each surgeon's performance by reverse coding patient risk-adjusted mortality rate into *patient risk-adjusted survival rate (RASR),* computed by subtracting patient risk-adjusted mortality rate from 1 (RASR=1 means the survival rate is 100%). To mitigate the risk of reverse causality, we measured *surgeons' patent RASR* at period *t*+1 and the independent and control variables at period *t*.

**Independent Variables.** Following the literature on learning from failures, we measured *surgeon's own accumulated failures* in a focal hospital as the total number of patient deaths experienced by a surgeon in a focal hospital up to period *t* (KC et al. 2013, Desai 2015).[4] Importantly, all accumulated experience variables in our study (including control variables) were discounted using a discount factor (λ) between 0 and 1, to take into account potential knowledge depreciation (Huesch 2009) and changes in intensity of negative emotions toward failures (Avgerinos et al. 2020).[5] We used the best-fit method used in prior studies to calculate the appropriate discount factor for each experience variable (see also Argote et al. 1990, Desai 2020). For *surgeon's own accumulated failures*, the calculated discount factor (λ) was 0.90. To test the curvilinear relationship hypothesized in H1, we included this variable and the squared term of it (termed "*surgeon's own accumulated failures sq*" hereafter) in our regression models.[6]

To test H2a, we created interaction terms between (1) *elite education* and *surgeon's own accumulated failures* and (2) *elite education* and *surgeon's own accumulated failures sq*. Cardiothoracic surgeons follow a standardized training path of medical school, general surgery residency, and cardiothoracic residency. Some also pursue advanced cardiothoracic fellowships. Our interviewees noted that surgeons receive their most important hands-on training during their cardiothoracic residency and fellowship, and thus the quality of training received at this level will greatly impact a surgeon's belief about their abilities to learn from failures. Following prior research (Burke et al. 2007, Greenwood et al. 2019), we used the U.S. News & World Report ranking to identify elite medical institutions and coded *elite education* as 1 if a surgeon completed a cardiothoracic surgery residency or fellowship at the top 30 best

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[4] We measured a surgeon's accumulated own failures at *each* hospital rather than across *all affiliated* hospitals because individuals' task experiences are suggested to be hospital-specific in this context (Huckman & Pisano, 2006).

[5] λ=0 means that the effect(s) of the experience depreciates immediately and λ=1 means that the effect(s) of the experience does not depreciate over time.

[6] Bennett and Snyder (2017) noted that using cumulative failures as an independent variable could trigger the "unit root problem" (Hamilton, 1994), which may bias results in models that test learning from failure. This concern is mitigated as we use time-discounted measure of accumulated failures (Dahlin et al., 2018). Furthermore, Fisher-type Phillips-Perron unit root test confirmed that the unit root problem is not an issue in our data.

hospitals for cardiology and heart surgery, and 0 otherwise.[7]

To test H2b, we constructed interaction terms between (1) *certified expertise* and *surgeon's own accumulated failures* and (2) *certified expertise* and *surgeon's own accumulated failures sq*. We coded surgeons who had the FACS designation at period *t* as having certified expertise. As mentioned earlier, to become a FACS, surgeons needed to meet exceptional qualification standards set by the College, and thus we expect those who have this designation to have higher (perceived) ability to learn from failures than surgeons who do not. Accordingly, we measured *certified expertise* as 1 if surgeons had the FACS designation in period *t*, and 0 otherwise.

To test H2c, we created interaction terms between (1) *specialization* and *surgeon's own accumulated failures* and (2) *specialization* and *surgeon's own accumulated failures sq*. As aforementioned, surgeons engage in various tasks including patient care, research, teaching, administration, telemedicine, and others. Surgeons who spend most time on patient care (i.e., specialize in surgery) are likely to have higher (perceived) ability to learn from surgery-related failures than surgeons who spend most time on other tasks. In our favor, the surgeons in our data reported to the Medical Board of California how much time they typically spent on the six tasks listed above. We coded *specialization* as 1 when surgeons spent most time on patient care among the six tasks, and 0 otherwise.[8]

**Control Variables.** We controlled for various individual and hospital level characteristics that can affect surgeons' performance. At the individual level, we first controlled for the number of *surgeon's accumulated isolated CABG surgeries* across all affiliated hospitals up to period *t* to control for surgeons' task experience (Reagans et al. 2005). Ideally, we would want to control for a surgeon's accumulated isolated CABG surgeries at the focal hospital because learning from surgeries has been suggested to be hospital specific (Huckman & Pisano, 2006). However, Bennett and Snyder (2017) strongly advised against including both

[7] These were hospitals ranked top 30 at least once during 2011-2014. 2011 was the first year that we had public access to the ranking data and 2014 was the latest cardiothoracic training completion year for our sample surgeons.
[8] We used survey responses from 2010 to 2016 because 2010 was the earliest available data. We imputed 2010 survey values for periods before 2010. The survey response rate was approximately 96%. Missing values were coded as spending zero hours on the task. H1 and H2c results were robust to dropping observations with missing values or using a measure created based on a single year response (year 2018).

accumulated successes and failures (and their linear combinations, which is a surgeon's accumulated isolated CABGs at the focal hospital) in models to test learning from failures because such approach could mechanically induce significant results even without real effects. Thus, we instead controlled for surgeons' accumulated isolated CABGs across all hospitals as a proxy of surgeons' task experience. All our hypotheses test results remained robust to controlling for surgeons' accumulated isolated CABGs at the focal hospital or surgeons' accumulated successes at the focal hospital (and their respective square terms) instead (Lapré & Cravey, 2022).

Next, because surgeons can learn from other surgeons' failures (KC et al. 2013), we controlled for the number of *surgeon's accumulated others' failures* measured as the accumulated number of failures by other surgeons in the same hospital. In addition, some surgeons might have performed more complex surgeries than others and thus had more learning opportunities (Stan and Vermeulen 2013). Because surgeons performed the same type of surgery in our context, surgery complexity mainly varied based on patients' conditions, reflected in the *expected number of patient deaths* data in the HCAI report. Thus, we controlled for *surgeon's average surgery complexity,* measured as a surgeon's number of expected patient deaths in a hospital accumulated up to period $t$ divided by a surgeon's number of isolated CABG surgeries performed in a hospital accumulated up to period $t$. Finally, we added *multiple hospital affiliation dummy* which captured whether a surgeon performed isolated CABG surgeries in multiple hospitals in period $t$ (KC and Tushe 2021).

At the hospital level, we first controlled for the number of *hospital's accumulated isolated CABG surgeries* up to period $t$ to capture a hospital's task experience (Reagans et al. 2005). Furthermore, we controlled for a hospital's experience in other types of surgeries (Clark and Huckman 2012), using the number of *hospital's accumulated inpatient surgeries* up to period $t$. As a surgeon may learn from other surgeons (KC et al. 2013), we controlled for *hospital's number of surgeons* who performed isolated CABG surgeries in a hospital in period $t$. A hospital with a trauma center or a cardiac intensive care unit (ICU) may learn more effectively by treating patients with complex conditions (Stan and Vermeulen 2013). Accordingly, we included *hospital's trauma dummy* coded as 1 if a hospital operated a trauma center in period *t* and 0 otherwise, and *hospital's cardiac ICU dummy*, coded as 1 if a hospital had at least one cardiac intensive care bed in period *t* and 0 otherwise. As a hospital's teaching status can affect patient care (Greenwood et al. 2017), we added *teaching hospital dummy*, which indicated whether a hospital was a teaching hospital defined by the American Hospital Association in period *t*. Because surgeon turnover can impact hospital-level knowledge and surgical outcomes (Thompson 2007), we also included a *surgeon turnover* measured as the proportion of isolated CABG performing surgeon who left a hospital during period *t*. Finally, because hospitals could learn from other hospitals (Desai 2015), we included the *number of hospitals in region* that offered isolated CABG surgeries in a hospital's region in period *t*. As noted earlier, all control variables related to accumulated experiences were discounted using appropriate discount factors (λ) between 0 and 1. Table 2.1 reports the descriptive statistics and correlations for all the variables included in our analyses.

- Insert Table 2.1 about here -

### 2.3.3 Econometric Models

Since our dependent variable (i.e., *surgeon's patient RASR*) is bounded by 0 and 1, we test our hypotheses using fractional logit regression models (Papke and Wooldridge 1996). Importantly, these log-linear models are most appropriate for our data, as some surgeons started accumulating surgery (and failure) experiences before the start of our data. Log-linear learning models have been used to yield unbiased coefficients when experience variables were left-censored in learning curve studies (Lapré and Tsikriktsis 2006, KC et al. 2013). Equation (1) shows the model for testing H1:

$$\begin{aligned} ln\left[\frac{E\left(Patient\ RASR_{i,h,t+1}\,\middle|\,\boldsymbol{X}\right)}{1-E\left(Patient\ RASR_{i,h,t+1}\,\middle|\,\boldsymbol{X}\right)}\right] &= \beta_0 + \beta_1 accum.own\ failures_{i,h,t} + accum.own\ failures_{i,h,t}{}^2 \\ &\quad + \beta_3 \boldsymbol{S_{i,t}} + \beta_4 \boldsymbol{H_{h,t}} + \lambda_{i,h} + \tau_t + u_{i,h,t} \end{aligned} \tag{1}$$

In this equation, $i$, $h$, and $t$ indicate surgeon, hospital, and period, respectively. The dependent variable was measured at period *t*+1 and the independent and control variables were measured at period *t* to mitigate reverse causality. $\boldsymbol{S_{i,t}}$ and $\boldsymbol{H_{h,t}}$ are vectors of individual- and hospital-level control variables. We also included surgeon-hospital dyad fixed effects ($\lambda_{i,h}$) and period fixed effects ($\tau_t$). Finally, we clustered the standard errors by surgeon-hospital dyads. By using fractional logit regression models, we essentially tested whether an inverted-U relationship exists between a surgeon's own accumulated failures and a surgeon's improvement in performance expressed as a logit-transformed expected surgeon's patient RASR.

We predicted that a surgeon's performance would improve up to a point and decrease afterwards as a function of accumulated failures. Thus, H1 will be supported if *surgeon's own accumulated failures* ($\beta_1$) has a positive coefficient and *surgeon's own accumulated failures sq* ($\beta_2$) has a negative and significant coefficient (Haans et al. 2016). $-\beta_1/2\beta_2$ is the inflection point at which surgeons cease learning.

Equation (2) shows the model that includes the interaction terms for testing H2a-c:

$$\begin{aligned} ln\left[\frac{E\left(Patient\ RASR_{i,h,t+1}\,\middle|\,\boldsymbol{X}\right)}{1-E\left(Patient\ RASR_{i,h,t+1}\,\middle|\,\boldsymbol{X}\right)}\right] \\ = \beta_0 + \beta_1 accum.own\ failures_{i,h,t} + \beta_2 accum.own\ failures_{i,h,t}{}^2 \\ + \beta_3 accum.own\ failures_{i,h,t} \times Z + \beta_4 accum.own\ failures_{i,h,t}{}^2 \times Z \\ + \beta_5 Z + \beta_6 \boldsymbol{S_{i,t}} + \beta_7 \boldsymbol{H_{h,t}} + \lambda_{i,h} + \tau_t + u_{i,h,t} \end{aligned} \quad (2)$$

In this equation, $Z$ represents *elite education*, *certified expertise*, and *specialization* for H2a-c, respectively. *Elite education* is time-invariant, and its single term will be dropped due to fixed effects. The inflection point for surgeons with low (perceived) ability to learn ($Z$=0) will form at $-\beta_1/2\beta_2$, whereas it will form at $-(\beta_1 + \beta_3)/\ 2(\beta_2 + \beta_4)$ for surgeons with high (perceived) ability to learn ($Z$=1). Because we hypothesize that the inflection point comes later for surgeons with higher (perceived) ability to learn than others, H2a-c will be supported if $-(\beta_1 + \beta_3)/\ 2(\beta_2 + \beta_4)$ is greater than $-\beta_1/2\beta_2$ **and** a Wald-type test rejects the null that the two inflection points are equal (i.e., $-\beta_1/2\beta_2 = -(\beta_1 + \beta_3)/\ 2(\beta_2 + \beta_4)$) (Medappa and Srivastava 2019).

**2.4 Results**

Table 2.2 shows the results of the analyses that test our hypotheses. Model 1 includes the control variables only. The positive relationship between *surgeon's accumulated others' failures* and *surgeon's patient RASR* suggests that surgeons learned from other surgeons' failures ($p$ = 0.02). In addition, s*urgeon's average surgery complexity* was positively associated with *surgeon's patient RASR* ($p$ < 0.01), implying that a surgeon learned more from performing complex surgeries than simple ones. Finally, *number of hospitals in region* was positively related to *surgeon's patient RASR* ($p$ = 0.02), suggesting that hospitals learned from other hospitals in the same region.

- Insert Table 2.2 about here -

To test the inverted-U relationship predicted in our H1, we included *surgeon's own accumulated failures* and *surgeon's own accumulated failures sq* in Model 2 of Table 2.2. The coefficient for *surgeon's own accumulated failures* was positive ($p$ < 0.01), and the coefficient for *surgeon's own accumulated failures sq* was negative ($p$ < 0.01), supporting H1. Figure 2.3 depicts the relationship between a surgeon's performance (the logit-transformed expected *surgeon's patient RASR*) at period $t$+1 and a *surgeon's own accumulated failures* up to period $t$ based on these results.

- Insert Figure 2.3 about here -

Performance increases until a surgeon experiences a certain number of patient deaths. However, after that point, the surgeon's performance decreases as more patient deaths are experienced. These results are consistent with our theory, which predicted that individuals' own accumulated failures and learning would have an inverted-U relationship because the opportunity to learn will increase but the motivation to learn will decrease as failures accumulate. The results were also consistent with our prediction that individuals will experience declining performance once they give up learning from their own failures because they will continue behaving in ways that led to failures and not modify or extend their existing knowledge although the task environment around them is changing.

To test H2a, we introduced interactions between (1) *surgeon's own accumulated failures* and *elite education* and (2) *surgeon's own accumulated failures sq* and *elite education* in Model 3 of Table 2.2. We were interested to see how the *inflection point* of the inverted-U relationship in H1 differed based on *elite education*. ***Unlike*** **conventional methods of moderation hypothesis testing in which interaction terms' coefficients are examined, testing the difference in inverted-U curves' inflection points (e.g., H2a-c) required computing the inflection points for a given pair of surgeon types based on coefficient estimates and examining whether the two inflection points statistically differed (see Medappa and**

**Srivastava 2019)**.[9] Therefore, as mentioned in the "Econometric models" section, we tested whether the inflection point for surgeons without elite education ($-\beta_1/2\beta_2$) occurred earlier than that for those with elite education ($-(\beta_1 + \beta_3)/\ 2(\beta_2 + \beta_4)$) and ran a Wald-type test to check if the two points were statistically different. Figure 2.4 depicts the results for H2a. Surgeons without elite education reached the learning inflection point earlier than those with elite education ($p = 0.02$), supporting H2a.

- Insert Figures 2.4, 2.5 and 2.6 about here -

Similarly, we tested H2b by including the interactions between (1) *surgeon's own accumulated failures* and *certified expertise* and (2) *surgeon's own accumulated failures sq* and *certified expertise* in Model 4 of Table 2.2. Figure 2.5 shows the results for H2b. Surgeons without certified expertise reached the inflection point sooner compared to surgeons with certified expertise ($p < 0.01$), supporting H2b.

Next, we tested H2c by adding the interactions between (1) *surgeon's own accumulated failures* and *specialization* and (2) *surgeon's own accumulated failures sq* and *specialization* in Model 5 of Table 2.2. Figure 2.6 illustrates the results for H2c. Again, surgeons who did not specialize in patient care reached the inflection point earlier than surgeons who specialized in patient care ($p < 0.01$), supporting H2c.

Finally, Model 6 of Table 2.2 shows the results of he full model including all interaction terms to test Hypotheses 2a-c. We found consistent support of Hypotheses 2a-c in this model ($p = 0.07$ for H2a; $p = 0.06$ for H2b; $p < 0.01$ for H2c). In sum, all our hypotheses were supported.

### 2.4.1 Qualitative Evidence Corroborating the Empirical Results

Based on these results, we returned to the qualitative data obtained through our 25 interviews with surgeons and physicians, to examine whether the experiences and views of our interviewees were consistent with our empirical findings. We found high consistency between the two. For example, related to the increase in *opportunities to learn* as failures accumulate, one surgeon told us:

> *Having more of an experience base allows you to see a pattern where a person with less experience, or fewer mistakes, or fewer complications might have a hard time seeing a pattern.*

Similarly, another surgeon highlighted the learning opportunities generated by each additional

[9] That is, testing H2a-c <u>does not</u> involve directly interpreting the statistical significance of the regression coefficients.

failure experience:

> *We may look the same, but inside, ischemic heart muscle, it has all these different coronaries with different blockages and stuff. ... And also the myocardium's different. ... So we discuss the physiology, the history of the operation, how it was performed, the pathophysiology and the pathology, what happened (each time a surgery does not go well).*

This was consistent with how a leading cardiac surgeon, Stephen Westaby, described the diversity of learning opportunities gained by each surgery in his autobiography *Open Heart* (2017):

> *There I found that every heart is different. Some are fat, some are lean. Some are thick, some are thin. Some are fast, some are slow. (p.5)*

Our interviews also revealed surgeons' motivation to learn from their own failures, especially from their earlier ones, despite feeling negative emotions from the failure. For example, describing his early failure, one physician explained:

> *If a person dies or goes to the ICU… it does wear on you because it's a person dying because of the mistake you've made. Then you have to talk to their family and cope with their reactions. So there's always that component of guilt and sadness. I think you need a day or two to process it emotionally. Then, you start thinking about what you could have done or like at least know what would have helped in those situations so that you don't make similar mistakes in the future.*

However, as negative emotions accumulated due to repeated failures, due to experiences such as the following one that one of our interviewees had, "(*At the hospital I used to work for,*) s*omeone would come up and say, 'Man you killed that patient,' and I took it so hard*," it seemed that some surgeons could fall into the state of helplessness. For example, one surgeon told us:

> *(After repeated failures) I would feel so frustrated. I would seriously doubt whether I deserve to be a surgeon. A few negative events could be learning opportunities but if it happens more than that, I don't think I qualify.*

This sort of helplessness seemed to eventually lead surgeons to cease learning from their failures. At the same time, we also found evidence of surgeons blaming their failures on other factors as they accumulated failures. For example, a surgeon explained:

> *(Once I had an error), and the error kind of centered around a very dramatic bleeding episode that took place immediately after an operation. There was some wiggle room as to whether it was a surgical technique problem … my ego made me look at all the other possible options and kind of cling to those to kind of protect my ego.*

Similarly, another physician explained:

*You play golf? It's like repeatedly slicing a ball into the woods, the water, or another fairway and coming back to the golf cart saying that you've used the wrong golf club or ball. Even if it's your fault you start blaming failures on other things because you think you've done enough. That is why people's golf stops improving. The same goes for surgery if you get into that mindset.*

Finally related to our finding that surgeons persist with learning when they perceive themselves to have high ability to learn from their failures, one surgeon mentioned:

*I went to a top 20 program ... people from our program would be upset at ourselves for making repeated mistakes and try to do better since we know it is possible, but they (surgeons from weaker programs) are not usually like that.*

Although our qualitative data does not qualify as a strict test for causality, our interviews were highly consistent with our empirical results and corroborated our proposed mechanisms. To further validate our results, we conduct robustness checks and additional analyses.

**2.4.2 Robustness Checks**

First, we confirmed H1's inverted-U relationship using procedures proposed by Lind and Mehlum (2010) (see also Haans et al. 2016). This analysis ruled out the possibility that the true relationship between accumulated failures and learning was only one half of an inverted-U; the slope of the curve was positive at the lower bound ($p < 0.01$) and negative at the upper bound ($p < 0.01$) of *surgeon's own accumulated failures*. In addition, the inflection point and the 95% confidence interval of the point were within the data range of *surgeon's own accumulated failures*. We also conducted a sensitivity analysis by excluding surgeon-hospital dyads with extreme *surgeon's accumulated own failures* values (i.e., 1$^{st}$ and 99$^{th}$ percentile cut-offs) and found robust results. Finally, we retested H1 using an Arellano-Bond linear dynamic panel model (an autoregressive model) that controlled for the dependent variable lagged by one time period, to control for the possibility that surgeons' past performance predicted their future performance. Results were robust.

Next, we reexamined all our hypotheses after limiting our sample to surgeons who worked in hospitals that did not offer cardiothoracic residency programs during the focal period. Although all surgeons confirmed that they were responsible for the patient deaths reported to the HCAI, it is possible that a resident performed a surgery instead of an attending surgeon as part of training. To rule this out, we identified hospitals offering thoracic residency programs from the Accreditation Council for Graduate Medical Education website and excluded those observations. Results in Table 2.3 show that all hypotheses were supported in this alternative test ($p < 0.05$).

- Insert Table 2.3 about here -

**2.5 Additional Analyses: Ruling in Proposed Mechanisms and Ruling out Alternative Explanations**

**2.5.1 Examination of learning from *others'* failures to test mechanisms driving H1**

We theorized in H1 that individuals' own accumulated failures and learning will have an inverted-U relationship because the opportunity to learn will increase but the motivation to learn will decrease as individuals fail more. Said differently, it is likely that individuals will continue to learn from their own failures if their motivation to learn did not drop as a function of accumulating failures (since the opportunities to learn would still be increasing). Although we do not have a direct way to measure changes in surgeons' motivation using our current data, examining learning from *other* surgeon's failures can provide useful insights for validating our proposed mechanisms. Experiencing other surgeons' failures would increase a surgeon's *opportunity to learn* (through vicarious learning), but would **not** affect the surgeon's *motivation to learn* (since experiencing others' accumulating failures is unlikely to evoke negative emotions or attribution biases). Based on this logic, we test the single- and squared-term effects of *surgeon's accumulated* ***others'*** *failures* on a *surgeon's patient RASR*. We expect the single-term coefficient to be positive and significant but the squared-term's coefficient to be statistically insignificant. These results would be consistent with the logic that surgeons' motivation to learn does not wear off when experiencing an increasing number of others' failures and that they will continue to learn from them since those failures continue to provide opportunities to learn. Table 2.4 presents the results of this test.

- Insert Table 2.4 about here -

Model 1 in Table 2.4 first shows the results of the regression that tests the effect of *surgeon's accumulated others' failures* on *surgeon's patient RASR*, while controlling for our original independent variables and covariates. The results show that surgeons learn from others' failures ($p = 0.02$). This is consistent with our prediction that, similar to one's own failures, others' failures provide individuals with the opportunity to learn. In Model 2, we added the squared term of *surgeon's accumulated others' failures* (i.e., *surgeon's accumulated others' failures sq*). The single term of *surgeon's accumulated others' failures* remained positive ($p$ = 0.08), but *surgeon's accumulated others' failures sq* was not statistically significant ($p$ = 0.47, highlighted in gray). These results are consistent with our argument that the results of H1 were driven by an interaction between the increasing opportunities to learn and decreasing motivation to learn from own failures.

**2.5.2 Were surgeons restricted from performing (certain) surgeries upon experiencing failures?**

We can imagine surgeons being restricted from performing further surgeries altogether if they are responsible for an increasing number of patient deaths, which in turn, could bias our data. To examine this possibility, we tested whether *surgeon's patient RASR* at a hospital at period $t$ predicted *surgeon's number of isolated CABG surgeries* at a hospital at period $t$+1, using a Poisson model with the same control variables and specifications as our original models (see Model 1 in Table 2.5 for results). The coefficient of *surgeon's patient RASR* was positive but insignificant ($p$ = 0.14), suggesting that there was no statistically meaningful relationship between the number of failures in the previous period and the number of surgeries surgeons performed in the next period.[10]

- Insert Table 2.5 about here -

However, it is possible that worse performing surgeons are precluded from performing *high-risk surgeries*, which would also bias our results if those surgeons experienced fewer failures due to only performing lower-risk surgeries. We examined this possibility by testing whether *surgeon's patient RASR* at a hospital at period $t$ positively predicted surgeons' patient *expected mortality rate* (the variable that reflects surgery complexity) at period $t$+1. The coefficient of *surgeon's patient RASR* was positive but not significant ($p$ = 0.36) (see Model 2 in Table 2.5). Overall, these results suggest that individuals who experienced more failures were *not* kept from performing additional surgeries or assigned to simpler

[10] One potential reason for this is that there are significantly more patients who need immediate cardiothoracic surgeries than surgeons who can perform them in a timely manner; thus, allowing them to perform surgeries will save more lives than restricting them from doing so.

surgeries in the next period.

### 2.5.3 Did surgeons with higher ability to learn perform more complex surgeries than others?

It is also possible that surgeons who received elite education, had certified expertise, and specialized in patient care performed more complex surgeries than other surgeons. Because performing complex surgeries could offer more learning opportunities (e.g., Stan and Vermeulen 2013), different learning opportunities instead of different levels of (perceived) ability to learn could have driven the results for H2a-c. Thus, to rule out this alternative explanation, we ran *t*-tests to investigate whether surgeons who did/did not have elite education, certified expertise, and specialization had statistically different patient *expected mortality rates* for their surgeries in each period. Results in Table 2.6 show that there was no systematic difference in the mean patient expected mortality rates between the two types of surgeons (only two results out of 21 tests were significant and the differences were in the opposite direction; see the cells highlighted in gray). Overall, we did not find convincing evidence to support this alternative explanation.

- Insert Table 2.6 about here -

### 2.5.4 Does surgeons' motivation to learn from their own failures decrease as they become more senior?

Finally, an alternative explanation for the decrease in motivation to learn from their own failures is that surgeons feel greater security as they become more senior. Because senior surgeons have relatively established professional status, they may not feel as pressured as junior surgeons to prove themselves and improve performance by learning from their failures. This would be a qualitatively different mechanism through which the motivation to learn from failures decreases compared to the ones we argued for. Contrary to this argument, the correlation between *surgeon's own accumulated failures* and a surgeon's professional tenure in our sample was low ($r = 0.20$), suggesting that surgeons who have accumulated many failures are not necessarily the ones who are more senior. Results for H1 were also robust to limiting our sample to junior surgeons with five or fewer years of professional tenure, who would not be subject to this alternative explanation.

## 2.6 Discussion and Conclusion

This paper set out to better understand learning from individuals' own failures, an important microfoundational process of organizational learning. Despite increasing attention to this process (KC et al. 2013, Eskreis-Winkler and Fishbach 2019, Wilhelm et al. 2019, Avgerinos et al. 2020, Lapré and Cravey 2022), existing theories and findings have been inconsistent: some studies theorized and documented positive effects of individuals' own failures on learning, whereas others theorized and found negative effects of such experiences on learning. In a recent review on this topic, Dahlin et al. (2018) emphasized that researchers should consider the interplay among three mechanisms—the opportunity, motivation, and ability to learn—jointly to better understand how individuals learn from failures. Responding to this call for sharper theoretical frameworks on failure learning, we develop and test a theoretical model on individual failure learning that mutually considers the effects of the opportunity, motivation, and ability to learn from failures.

In specific, we theorize that the relationship between an individual's own accumulated failures and learning will form an inverted-U shape—driven by opposing forces between an individual's opportunity and motivation to learn as failures accumulate—and that this relationship will be moderated by the individual's (perceived) ability to learn. Using extensive panel data on 307 cardiothoracic surgeons who performed isolated CABG surgeries in California across 16 years, we find support for our hypotheses. To the best of our knowledge, ours is the first paper in this literature to document a curvilinear main relationship between an individual's own accumulated failures and learning, and we believe it has important implications.

To begin with, future studies examining individual-level failure learning should consider setting this inverted-U relationship between individuals' own failures and learning as a baseline theoretical prediction, especially in contexts where failures occur repeatedly (e.g., KC et al. 2013, Wilhelm et al. 2019, Avgerinos et al. 2020, Lapré and Cravey 2022). In fact, it could be that some prior studies found positive effects of individual failure learning whereas others found negative effects because of the particular samples that were used. If the sample was one where individuals had very few or too many accumulated failures, the results would show limited or no learning from one's own additional failures according to our theory (e.g., KC et al. 2013). On the contrary, if the sample was one where individuals had moderate levels of accumulated failures, the results would show considerable learning (e.g., Lapré and Cravey 2022). Thus, at the minimum, researchers studying individual-level failure learning in the future should consider the range of accumulated failures that individuals in their contexts can experience when developing their theory.

A more nuanced implication is that not all experiences necessarily lead to learning, and they can even be detrimental to learning. The experiential learning literature has often viewed an experience as a beneficial source of learning (see Argote et al. 2021 for a review). However, this may not hold for all types of experiences, especially ones that can elicit negative emotions or attribution biases such as failures. In fact, research has shown that even some positive experiences could deteriorate learning (Schumacher et al. 2020). In this sense, we believe it is crucial for learning researchers to consider not only the opportunities for learning that experiences bring, but also other consequences that they lead to, such as changes in the motivation to learn.

In addition, we also find heterogeneity in the degree to which individuals learn from failures, which seems to be driven by varying individuals' (perceived) ability to learn. Specifically, we find that the point at which individuals cease learning from their own failures varies according to their education, expertise, and specialization. We theorized that these factors would affect individuals' (perceived) ability to learn, and that individuals with higher (perceived) ability to learn will be more persistent in learning from their own failures than their counterparts. In our context, we found that surgeons with elite education, with certified expertise, and who specialized in patient care persisted in learning from their own failures longer than their counterparts.

These results are also meaningful because they have implications for learning at the organizational level. Organizations are aggregates of individuals; hence, learning by individuals will affect organizational learning. What may seem like a variance in learning rates across organizations could be driven by different learning rates of individuals within the organizations. Thus, understanding how to improve individuals' learning would be useful for improving organizational performance. Our results suggest that individuals' motivation to learn is an important mechanism for learning from failures and that individuals who have qualifications or past experiences associated with higher (perceived) ability to learn will have higher motivation to learn, and thus persist longer in learning. While our study focused only on individual learning from their own failures to understand this baseline relationship more deeply, future studies could extend this study to examine how multiple individual-level learning processes aggregate to affect organizational outcomes. For example, individuals' decrease in motivation to learn from their own repeated failures could potentially impact other individuals' vicarious learning processes. When individuals disassociate from their own failures or make erroneous attribution of the causes of their own failures, they will not be able to provide the opportunity for their colleagues to learn from their failures. This negative spillover effect could further damage organizational performance.

Naturally, these results have implications for organization design and strategic human capital management, especially in the areas of hiring and training. Future research could shed further light on these organizational factors that can help individuals be more resilient to negative effects of failures. It is no surprise that organizations tend to focus on the attributes of job applicants that signal their chances of success in the organization when making hiring decisions. However, our results suggest that it is important for hiring organizations to also consider attributes that make individuals more resilient to failures, especially in organizations where repeated failures are inevitable (e.g., R&D labs, start-ups, etc.). For example, in addition to the perceived ability to learn examined in this paper, individuals with high humility were found to be more willing to learn from negative feedback (Seckler et al. 2021). Our results also imply that training will be important for employees to learn more from their failures. The literature on self-efficacy has demonstrated that self-efficacy can be trained (Eden and Aviram 1993, Davis et al. 2000, Salas and Cannon-Bowers 2001). Relatedly, organizational culture that emphasizes positive employee morale and a growth mindset has been found to encourage individuals to frame errors as learning opportunities (Dahl and Werr 2021). Thus, we expect that organizations which provide self-efficacy training or have a growth mindset could assist employees in persisting longer in learning from their failures and in contributing more to organizational performance.

Notably, our findings come with some caveats. First, it is needless to say that failures occur in different forms across different contexts. Our context is one in which failures are relatively rare, high-stake events that involve patient deaths. Hence, the negative emotions triggered by these failures or the likelihood of attribution biases are likely to be larger than when the stakes are not as high. For example, some studies have examined near-misses or errors (Dillon and Tinsley 2008, Ramanujam and Goodman 2011, Madsen et al. 2016) or less severe failures such as product recalls (Haunschild and Rhee 2004). Although we predict that the processes we theorized in our paper will occur similarly in most failure-related situations (albeit to different degrees), more research is needed to examine the learning outcomes of experiencing different types of errors or failures such as the ones mentioned above. Second, our context is one where failures were sometimes out of control of the individual. These contexts could make it easier for individuals to attribute their failures to external causes. In addition, our setting is one where accumulating failure do not lead to the immediate termination of the individual from the organization. As these factors could affect individuals' motivation to learn from failures, it would be useful to see future papers examining the relationship in other contexts where individuals have more control over their failures and can be terminated from their organizations more easily (e.g., Park et al. 2022).

Third, our study could have benefitted from using more fine-grained, surgery-level data, since it would have enabled us to examine individual learning patterns in greater granularity. Unfortunately, the HCAI did not publicly offer such data. Nevertheless, one important advantage of our data is that it includes significantly more failures than prior studies (e.g., approximately four times the amount in KC et al. 2013 who studied a similar topic but using surgery-level data), and thus would be able to capture the effects of accumulated failures at higher ranges. Finally, due to data limitations, we could not directly measure or manipulate our theoretical mechanisms. We considered running lab experiments, but manipulating the effects of failures, especially ones that significantly matter to the subject and those that repeat over time, did not seem feasible nor realistic in a lab environment. To offset this limitation, however, we complemented our empirical results with qualitative interview data and conducted an array of additional analyses to rule in our theorized mechanisms and rule out alternative mechanisms. Notwithstanding, we encourage future studies to investigate the mechanisms in further depth using contexts that allow for stronger identification.

Overall, we believe that our research makes several meaningful contributions to the literature on individual failure learning and organizational learning. We especially hope that our paper sheds new light on the relationship between individuals' own failures and learning and opens exciting opportunities for understanding the micro-processes of organizational learning.

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## 2.8 Tables and Figures

**Table 2.1** Descriptive Statistics and Correlations ($n$ = 2,808)

| | Variables | Mean | SD | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Surgeon's patient RASR | 0.974 | 0.060 | 0.000 | 1.000 | | | | | | |
| 2 | Surgeon's accum. own failures (discounted) | 4.590 | 5.459 | 0.000 | 36.869 | 0.017 | | | | | |
| 3 | Elite education | 0.535 | 0.499 | 0.000 | 1.000 | 0.040 | 0.001 | | | | |
| 4 | Certified expertise | 0.595 | 0.491 | 0.000 | 1.000 | 0.001 | 0.053 | 0.032 | | | |
| 5 | Specialization | 0.935 | 0.246 | 0.000 | 1.000 | -0.017 | 0.088 | 0.045 | 0.069 | | |
| 6 | Surgeon's accum. iso-CABG surgeries (000s, discounted) | 0.222 | 0.142 | 0.001 | 0.771 | 0.083 | 0.424 | 0.052 | 0.153 | 0.145 | |
| 7 | Surgeon's accum. others' failures (discounted) | 5.209 | 5.569 | 0.000 | 61.000 | 0.010 | 0.089 | 0.018 | -0.105 | 0.032 | 0.108 |
| 8 | Surgeon's average surgery complexity | 0.026 | 0.015 | 0.002 | 0.463 | 0.023 | 0.040 | 0.008 | 0.030 | 0.029 | -0.032 |
| 9 | Multiple hospital affiliation dummy | 0.771 | 0.420 | 0.000 | 1.000 | -0.004 | -0.169 | -0.067 | 0.056 | 0.087 | 0.223 |
| 10 | Hospital's accum. iso-CABG surgeries (000s, discounted) | 1.070 | 1.091 | 0.002 | 7.670 | 0.055 | 0.411 | 0.084 | -0.074 | 0.032 | 0.277 |
| 11 | Hospital's accum. inpatient surgeries (000s, discounted) | 35.093 | 28.560 | 0.202 | 192.706 | 0.037 | 0.130 | 0.108 | 0.020 | -0.123 | -0.118 |
| 12 | Hospital's number of surgeons | 5.340 | 2.180 | 1.000 | 13.000 | 0.011 | -0.110 | 0.060 | -0.033 | -0.053 | 0.039 |
| 13 | Hospital's trauma center dummy | 0.312 | 0.463 | 0.000 | 1.000 | -0.007 | -0.009 | 0.031 | 0.007 | -0.101 | -0.101 |
| 14 | Hospital's cardiac ICU dummy | 0.755 | 0.430 | 0.000 | 1.000 | 0.029 | 0.086 | 0.074 | -0.018 | 0.005 | -0.016 |
| 15 | Teaching hospital dummy | 0.450 | 0.498 | 0.000 | 1.000 | 0.028 | -0.008 | 0.007 | 0.068 | -0.070 | -0.145 |
| 16 | Surgeon turnover | 0.162 | 0.175 | 0.000 | 0.833 | -0.035 | -0.048 | -0.079 | -0.020 | -0.032 | -0.038 |
| 17 | Number of hospitals in region | 18.274 | 7.726 | 8.000 | 28.000 | 0.010 | -0.120 | 0.024 | -0.007 | -0.087 | -0.207 |

| | Variables (Continued) | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | Surgeon's average surgery complexity | 0.049 | | | | | | | | | |
| 9 | Multiple hospital affiliation dummy | -0.061 | 0.034 | | | | | | | | |
| 10 | Hospital's accum. iso-CABG surgeries (000s, discounted) | 0.343 | -0.119 | -0.177 | | | | | | | |
| 11 | Hospital's accum. inpatient surgeries (000s, discounted) | -0.054 | -0.101 | -0.309 | 0.420 | | | | | | |
| 12 | Hospital's number of surgeons | 0.407 | 0.030 | 0.085 | 0.279 | 0.165 | | | | | |
| 13 | Hospital's trauma center dummy | -0.049 | -0.002 | -0.139 | -0.035 | 0.325 | 0.050 | | | | |
| 14 | Hospital's cardiac ICU dummy | 0.139 | -0.027 | -0.135 | 0.219 | 0.257 | 0.137 | 0.139 | | | |
| 15 | Teaching hospital dummy | 0.048 | -0.006 | -0.160 | 0.189 | 0.410 | 0.210 | 0.268 | 0.222 | | |
| 16 | Surgeon turnover | 0.006 | 0.003 | 0.015 | -0.044 | -0.010 | 0.287 | 0.046 | 0.021 | 0.030 | |
| 17 | Number of hospitals in region | -0.112 | 0.018 | -0.012 | -0.103 | 0.040 | 0.027 | -0.070 | -0.083 | 0.093 | 0.042 |

**Table 2.2** Fractional Logit Regression Estimates for Surgeon's Patient Risk-adjusted Survival Rate

| **DEPENDENT VARIABLE: Surgeon's patient RASR (period *t*+1)** | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| **INDEPENDENT VARIABLES (period *t*)** | | | | | | |
| Surgeon's own accum. failures **(H1)** | | $0.245^{**}$ | $0.301^{**}$ | $0.310^{**}$ | $0.640^{**}$ | $0.724^{**}$ |
| | | (0.036) | (0.049) | (0.047) | (0.180) | (0.183) |
| Surgeon's own accum. failures sq **(H1)** | | $-0.005^{**}$ | $-0.007^{**}$ | $-0.008^{**}$ | $-0.032^{**}$ | $-0.035^{**}$ |
| | | (0.001) | (0.002) | (0.002) | (0.011) | (0.011) |
| Surgeon's own accum. failures **(H2a)** | | | $-0.094^{*}$ | | | $-0.091^{*}$ |
| **x** Elite education | | | (0.044) | | | (0.042) |
| Surgeon's own accum. failures sq **(H2a)** | | | $0.004^{*}$ | | | $0.004^{**}$ |
| **x** Elite education | | | (0.002) | | | (0.001) |
| Surgeon's own accum. failures **(H2b)** | | | | $-0.090^{*}$ | | $-0.084^{*}$ |
| **x** Certified expertise | | | | (0.042) | | (0.042) |
| Surgeon's own accum. failures sq **(H2b)** | | | | $0.004^{*}$ | | $0.004^{*}$ |
| **x** Certified expertise | | | | (0.002) | | (0.002) |
| Surgeon's own accum. failures **(H2c)** | | | | | $-0.397^{*}$ | $-0.366^{*}$ |
| **x** Specialization | | | | | (0.175) | (0.178) |
| Surgeon's own accum. failures sq **(H2c)** | | | | | $0.027^{*}$ | $0.025^{*}$ |
| **x** Specialization | | | | | (0.011) | (0.011) |
| Certified expertise | | -0.033 | -0.040 | 0.208 | -0.031 | 0.172 |
| | | (0.217) | (0.221) | (0.277) | (0.218) | (0.281) |
| Specialization | | 0.290 | 0.286 | 0.321 | $1.175^{*}$ | $1.102^{*}$ |
| | | (0.259) | (0.254) | (0.256) | (0.561) | (0.561) |
| **CONTROL VARIABLES (period *t*)** | | | | | | |
| Surgeon's accum. iso-CABG surgeries | 0.618 | $-1.713^{*}$ | $-1.756^{*}$ | $-1.888^{*}$ | $-1.907^{*}$ | $-2.090^{**}$ |
| | (0.672) | (0.783) | (0.787) | (0.812) | (0.781) | (0.807) |
| Surgeon's accum. others' failures | $0.029^{*}$ | $0.029^{*}$ | $0.027^{*}$ | $0.029^{*}$ | $0.027^{*}$ | $0.026^{*}$ |
| | (0.013) | (0.012) | (0.013) | (0.013) | (0.012) | (0.013) |
| Surgeon's average surgery complexity | $22.012^{**}$ | $20.441^{**}$ | $20.177^{**}$ | $19.855^{**}$ | $20.012^{**}$ | $19.222^{**}$ |
| | (7.190) | (7.445) | (7.433) | (7.448) | (7.470) | (7.461) |
| Multiple hospital affiliation dummy | -0.210 | -0.164 | -0.158 | -0.186 | -0.171 | -0.184 |
| | (0.221) | (0.220) | (0.220) | (0.222) | (0.223) | (0.223) |
| Hospital's accum. iso-CABG surgeries | 0.046 | -0.037 | -0.060 | -0.038 | -0.032 | -0.058 |
| | (0.115) | (0.117) | (0.119) | (0.119) | (0.116) | (0.121) |
| Hospital's accum. inpatient surgeries | 0.001 | 0.004 | 0.004 | 0.003 | 0.003 | 0.004 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Hospital's number of surgeons | -0.074 | $-0.088^{\dagger}$ | $-0.089^{\dagger}$ | $-0.085^{\dagger}$ | $-0.084^{\dagger}$ | $-0.084^{\dagger}$ |
| | (0.046) | (0.047) | (0.047) | (0.047) | (0.047) | (0.047) |
| Hospital's trauma dummy | 0.066 | -0.053 | -0.039 | -0.060 | -0.049 | -0.044 |
| | (0.185) | (0.194) | (0.195) | (0.195) | (0.193) | (0.196) |
| Hospital's cardiac ICU dummy | 0.073 | 0.108 | 0.116 | 0.096 | 0.110 | 0.106 |
| | (0.162) | (0.172) | (0.171) | (0.172) | (0.172) | (0.170) |
| Teaching hospital dummy | 0.234 | 0.298 | 0.301 | 0.302 | 0.284 | 0.290 |
| | (0.201) | (0.207) | (0.210) | (0.207) | (0.208) | (0.210) |
| Surgeon turnover | -0.369 | -0.174 | -0.184 | -0.175 | -0.199 | -0.206 |
| | (0.398) | (0.400) | (0.398) | (0.401) | (0.403) | (0.401) |
| Number of hospitals in region | $0.120^{*}$ | $0.100^{\dagger}$ | $0.104^{\dagger}$ | $0.096^{\dagger}$ | $0.093^{\dagger}$ | $0.095^{\dagger}$ |
| | (0.050) | (0.053) | (0.054) | (0.053) | (0.053) | (0.053) |
| Constant | 0.683 | $1.461^{\dagger}$ | $1.475^{\dagger}$ | 1.283 | 0.693 | 0.630 |
| | (0.752) | (0.824) | (0.825) | (0.827) | (0.927) | (0.924) |
| Period and Surgeon-Hospital FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,808 | 2,808 | 2,808 | 2,808 | 2,808 | 2,808 |
| Number of Clusters | 636 | 636 | 636 | 636 | 636 | 636 |

*Notes.* Robust standard errors clustered by surgeon-hospital are in parentheses. *Elite education* is omitted due to collinearity. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

**Table 2.3** Fractional Logit Regression Estimates for Surgeon's Patient RASR Using Sample of Surgeons who Worked in Hospitals without Cardiothoracic Residency Programs

| **DEPENDENT VARIABLE: Surgeon's patient RASR (period *t*+1)** | ***Sample:*** *Surgeons who worked in hospitals that did not offer cardiothoracic residency programs* | | | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| **INDEPENDENT VARIABLES (period *t*)** | | | | |
| Surgeon's own accum. failures | $0.235^{**}$ | $0.295^{**}$ | $0.307^{**}$ | $0.614^{**}$ |
| | (0.036) | (0.049) | (0.046) | (0.224) |
| Surgeon's own accum. failures sq **(H1)** | $-0.005^{**}$ | $-0.007^{**}$ | $-0.008^{**}$ | $-0.030^{*}$ |
| | (0.001) | (0.002) | (0.001) | (0.014) |
| Surgeon's own accum. failures **(H2a)** | | $-0.105^{*}$ | | |
| **x** Elite education | | (0.044) | | |
| Surgeon's own accum. failures sq **(H2a)** | | $0.004^{*}$ | | |
| **x** Elite education | | (0.002) | | |
| Surgeon's own accum. failures **(H2b)** | | | $-0.100^{*}$ | |
| **x** Certified expertise | | | (0.043) | |
| Surgeon's own accum. failures sq **(H2b)** | | | $0.004^{**}$ | |
| **x** Certified expertise | | | (0.002) | |
| Surgeon's own accum. failures **(H2c)** | | | | $-0.381^{\dagger}$ |
| **x** Specialization | | | | (0.222) |
| Surgeon's own accum. failures sq **(H2c)** | | | | $0.025^{\dagger}$ |
| **x** Specialization | | | | (0.014) |
| Certified expertise | -0.091 | -0.107 | 0.227 | -0.071 |
| | (0.205) | (0.209) | (0.274) | (0.206) |
| Specialization | 0.192 | 0.186 | 0.225 | 1.140 |
| | (0.310) | (0.304) | (0.306) | (0.749) |
| Control Variables | Yes | Yes | Yes | Yes |
| Period and Surgeon-Hospital Dyad FEs | Yes | Yes | Yes | Yes |
| Observations | 2,376 | 2,376 | 2,376 | 2,376 |
| Number of Clusters | 529 | 529 | 529 | 529 |

*Notes.* Robust standard errors clustered by surgeon-hospital are in parentheses. *Elite education* is omitted due to collinearity. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

**Table 2.4** Fractional Logit Regression Estimates for Surgeon's Patient RASR Which Examines the Relationship Between Others' Accumulated Failures and Surgeon's Patient RASR

| **DEPENDENT VARIABLE: Surgeon's patient RASR (period *t*+1)** | Model 1 | Model 2 |
|---|---|---|
| **INDEPENDENT VARIABLES (period *t*)** | | |
| Surgeon's accum. own failures | $0.245^{**}$ | $0.245^{**}$ |
| | (0.036) | (0.036) |
| Surgeon's accum. own failures sq | $-0.005^{**}$ | $-0.005^{**}$ |
| | (0.001) | (0.001) |
| Surgeon's accum. others' failures | $0.029^{*}$ | $0.038^{\dagger}$ |
| | (0.012) | (0.021) |
| Surgeon's accum. others' failures sq | | -0.0003 |
| | | (0.0004) |
| Control Variables | Yes | Yes |
| Period and Surgeon-Hospital FEs | Yes | Yes |
| Observations | 2,808 | 2,808 |
| Number of Clusters | 636 | 636 |

*Note.* Robust standard errors clustered by surgeon-hospital are in parentheses. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

**Table 2.5** Conditional Fixed-effects Poisson Regression Estimates for Surgeon's Number of Isolated CABG Surgeries Performed at Focal Hospital (Model 1) and Fractional Logit Regression Estimates for Surgeon's Patient Expected Mortality Rate at Focal Hospital (Model 2)

| | ***DV:*** *Surgeon's number of isolated CABG surgeries (period t+1)* | ***DV:*** *Surgeon's patient expected mortality rate (period t+1)* |
|---|---|---|
| | Model 1 | Model 2 |
| **INDEPENDENT VARIABLES (period *t*)** | | |
| Surgeon's patient RASR | 0.625 | 0.350 |
| | (0.423) | (0.379) |
| Control Variables | Yes | Yes |
| Period and Surgeon-Hospital Dyad FEs | Yes | Yes |
| Observations | 3,078 | 2,808 |
| Number of Clusters | 636 | 636 |

*Notes.* Robust standard errors clustered by surgeon-hospital are in parentheses. For Model 1, we included the 270 observations of surgeons who performed surgeries in period *t* but left their jobs in period *t*+1. Surgeon's number of isolated CABG surgeries were coded as 0 for these observations as if they were still employed but were not allowed to perform any surgeries.

**Table 2.6** Mean Patient Expected Mortality Rates (EMR) Difference Tests to Examine Whether Surgeons who Differed in Education, Certified Expertise, and Specialization Performed Surgeries with Different Complexity Levels

| **Period** | **Elite Education** | | | **Certified Expertise** | | | **Specialization** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **(1) Yes** | **(2) No** | **(1)-(2) Difference** | **(3) Yes** | **(4) No** | **(3)-(4) Difference** | **(5) Yes** | **(6) No** | **(5)-(6) Difference** |
| 03-04 | 3.22 | 3.11 | 0.11 | 3.02 | 3.40 | -0.38$^{*}$ | 3.16 | 3.31 | -0.15 |
| 05-06 | 2.86 | 2.71 | 0.15 | 2.92 | 2.61 | 0.31 | 2.80 | 2.72 | 0.08 |
| 07-08 | 2.27 | 2.34 | -0.07 | 2.31 | 2.28 | 0.03 | 2.32 | 1.98 | 0.34 |
| 09-10 | 1.92 | 1.94 | -0.02 | 1.89 | 1.97 | -0.08 | 1.93 | 1.87 | 0.06 |
| 11-12 | 2.00 | 2.10 | -0.10 | 2.06 | 2.03 | 0.03 | 2.05 | 2.03 | 0.02 |
| 13-14 | 2.05 | 2.06 | -0.01 | 2.08 | 2.02 | 0.06 | 2.06 | 1.94 | 0.12 |
| 15-16 | 2.40 | 2.68 | -0.28$^{\dagger}$ | 2.47 | 2.61 | -0.14 | 2.55 | 2.35 | 0.20 |

*Notes.* Each cell value represents the mean patient expected mortality rate (EMR) for surgeons in each category during the period. A higher EMR implies a more severe patient condition. Because independent variables were lagged, the last sample period's observations were not included in the table. $^{\dagger}p < 0.1$; $^{*}p < 0.05$.

**Figure 2.1** Summary of (1) How the Opportunity and Motivation to Learn from One's Own Failures change as a Function of Accumulated Failures and (2) How the Two Mechanisms Interact to Affect an Individual's Learning from Those Failures

| One's own accumulated failures | Opportunity x Motivation to learn from one's own failures | Learning |
|---|---|---|
| Low | Low opportunity x High motivation | Low |
| Moderate | Moderate opportunity x Moderate motivation | Peak |
| High | High opportunity x Low motivation | Low |

**Figure 2.2** Illustration of the Relationship Between Individuals' Own Accumulated Failures and Individual Learning Based on Individuals' (Perceived) Ability to Learn Levels

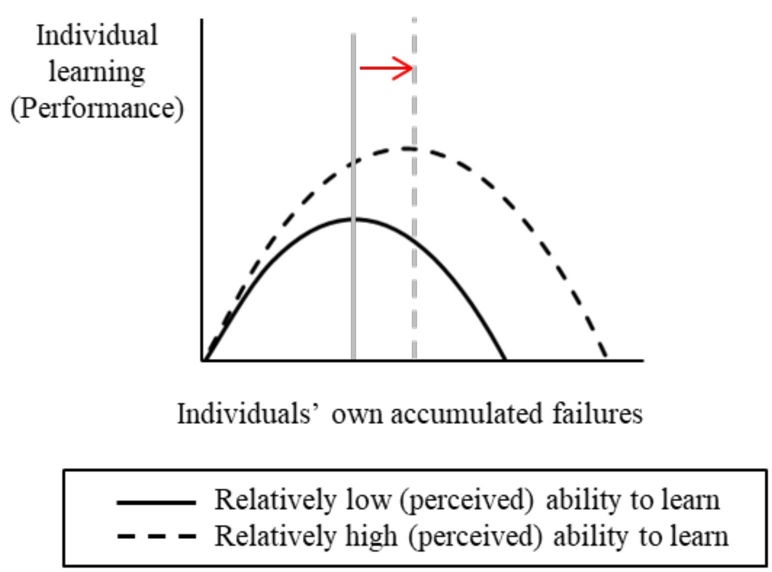
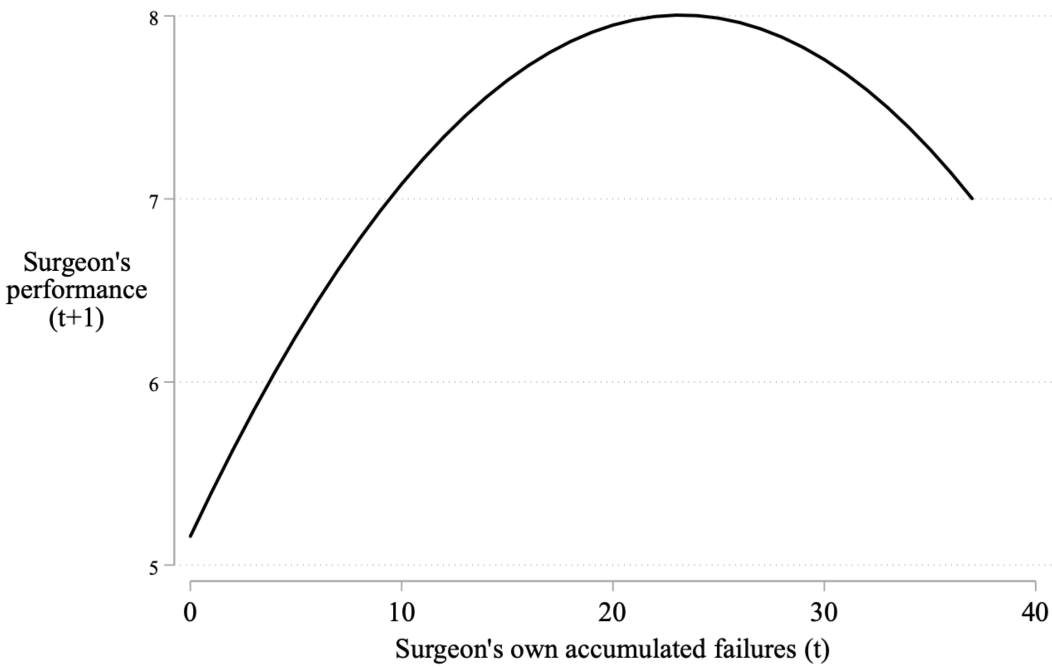
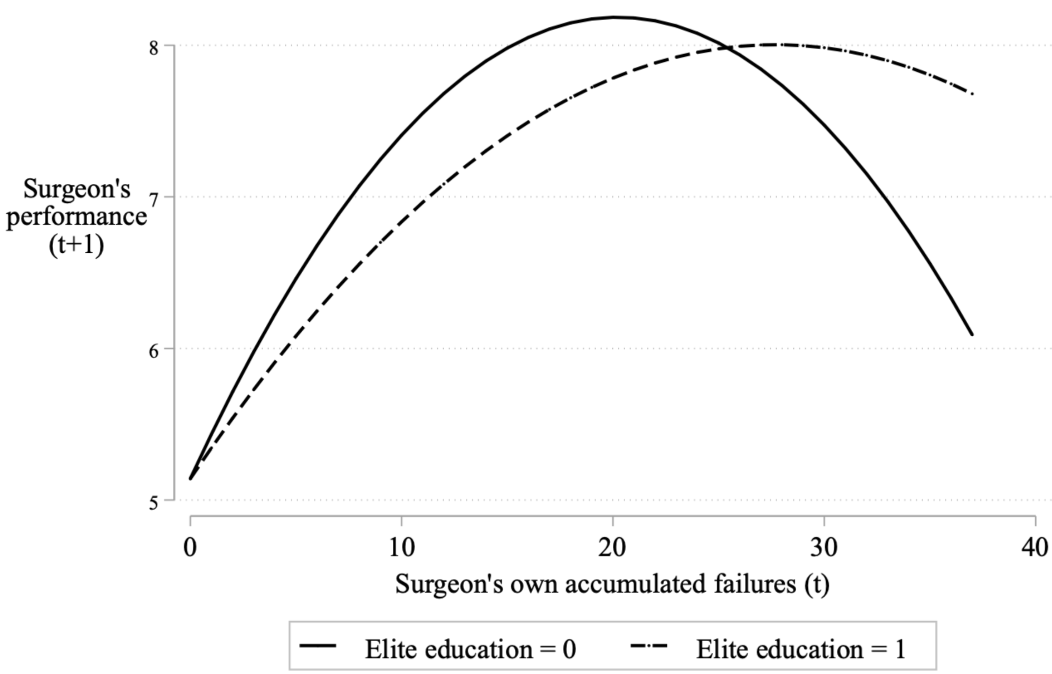


**Figure 2.3** Relationship Between Surgeon's Own Accumulated Failures and Surgeon's Performance



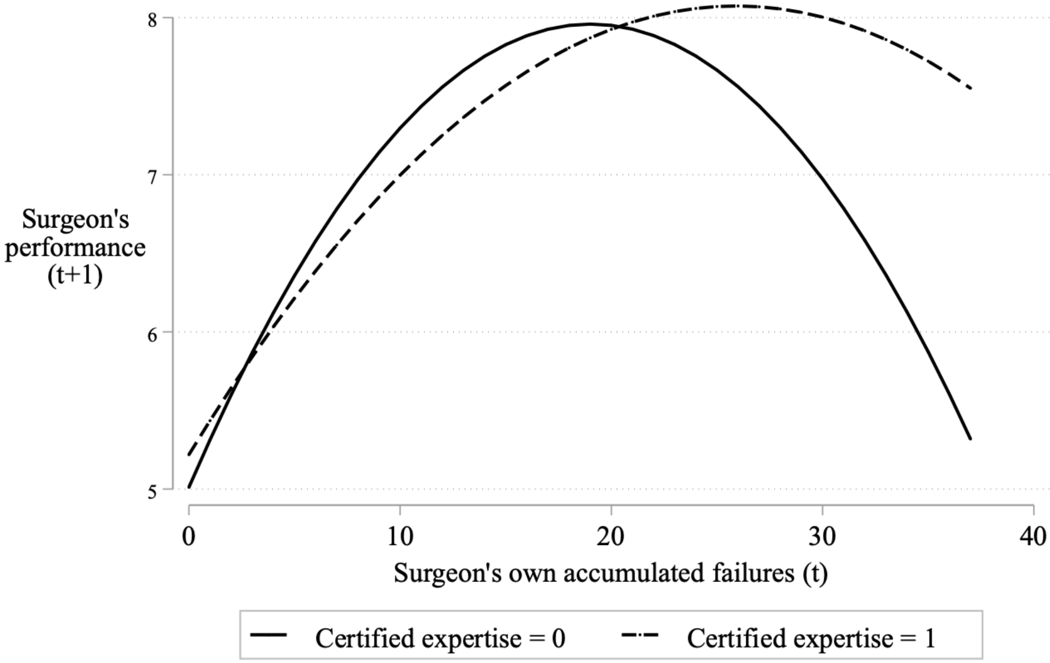

*Note.* Surgeon's performance is expressed as logit-transformed expected surgeon's patient RASR.

**Figure 2.4** Relationship Between Surgeon's Own Accumulated Failures and Surgeon's Performance Moderated by Elite Education



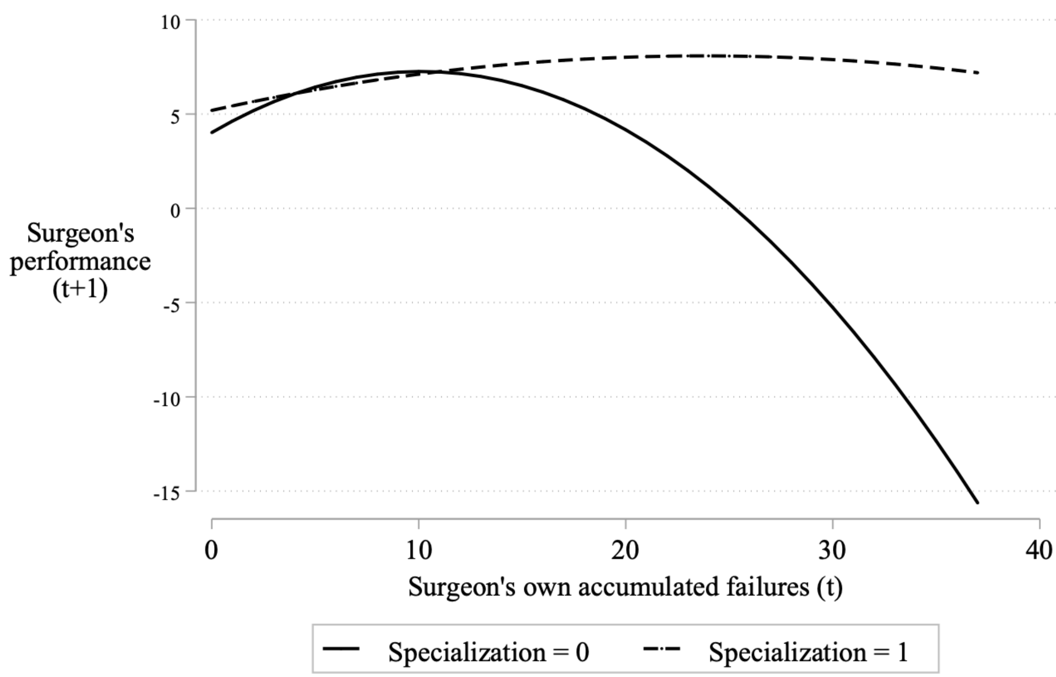

*Note.* Surgeon's performance is expressed as logit-transformed expected surgeon's patient RASR.

**Figure 2.5** Relationship Between Surgeon's Own Accumulated Failures and Surgeon's Performance Moderated by Certified Expertise




*Note.* Surgeon's performance is expressed as logit-transformed expected surgeon's patient RASR.

**Figure 2.6** Relationship Between Surgeon's Own Accumulated Failures and Surgeon's Performance Moderated by Specialization




*Note.* Surgeon's performance is expressed as logit-transformed expected surgeon's patient RASR.

# CHAPTER 3. HOW EMPLOYING CONTRACTORS AFFECTS ORGANIZATIONAL LEARNING: EVIDENCE FROM U.S. HOSPITALS

**Abstract**

This study examines the conditions under which using contractors facilitates organizational learning in terms of organizations' adoption of an industry's new best practices. Contractors—who provide services to clients based on contracts—often work simultaneously across multiple organizations. While contractors can bring diverse knowledge from other organizations to facilitate implementing new practices, contractors lack firm-specific knowledge about implementing those practices. By contrast, although full-time employees have firm-specific knowledge, they typically have less exposure to diverse knowledge possessed by other organizations. Drawing from minority-majority relations theories, I hypothesize that organizational learning will peak when organizations use a moderate proportion of contractors. This is because the relationship between full-time employees and contractors will be the most positive at this point, facilitating the transfer of firm-specific knowledge and diverse knowledge between the two. I test this hypothesis in the healthcare context, where an important guideline on using stents was promulgated in 2006, and organizations had to learn this new best practice. I find evidence for my hypothesis using data on 85,567 patients treated in 40 New York state hospitals between 2004 and 2007. In addition, I test my theorized mechanisms by showing that organizations with a low or high proportion of contractors can facilitate learning by using specific contractors who can mitigate their knowledge transfer barriers. This paper contributes to research on knowledge transfer, organizational learning, and strategic human capital.

## 3.1 Introduction

Employee mobility has been discussed as an important mechanism through which organizational learning occurs (Argote and Ingram 2000, Mawdsley and Somaya 2016, Kane and Rink 2020, Argote et al. 2021). Individuals can potentially transfer diverse forms of knowledge—tacit and explicit—from one organization to another and adapt the transferred knowledge to fit the recipient units (Argote and Ingram 2000, Mawdsley and Somaya 2016). The knowledge transferred by individuals can also facilitate the creation of new knowledge, leading to increased innovation and performance (Boeker 1997, Rosenkopf and Almeida 2003, Song et al. 2003, Jain 2016, Kolympiris et al. 2019, Stadler et al. 2022).

Many studies of employee mobility implicitly assume that knowledge effectively transfers from one organization to another when individuals move. Several studies, however, have found that individuals who move and individuals in the recipient units do not always transfer knowledge to each other (Szulanski 1996, Kane et al. 2005, Singh and Agrawal 2011, Jain 2016, Slavova et al. 2016). For example, Singh and Agrawal (2011) found that while organizations appeared to be using the new hires' knowledge, this was mainly driven by new hires' use of their own knowledge. Importantly, individuals who move and those in the recipient units may lack the motivation to share or utilize the knowledge shared by their counterparts (Argote 2013, Szulanski and Lee 2020). These studies highlight the need for a better understanding of when individuals who move can effectively transfer their knowledge to recipient units.

At the same time, organizations often use contractors alongside full-time employees. Contractors contract with clients or contract firms to provide services to clients (Katz and Krueger 2019). Contractors have been used in many industries. This paper specifically focuses on contractors who work in knowledge-intensive professions. These contractors usually work alongside and perform the same tasks as full-time employees (Bidwell et al. 2013, Barley et al. 2017). However, they maintain arm's length relationships with firms. Naturally, contractors tend to split their time across multiple organizations, have limited employment durations, and often lack access to employee-only activities such as training (Lautsch 2002, Huckman and Pisano 2006). Organizations typically use contractors to respond to fluctuating demands or temporarily access specialized skills (Davis-Blake and Uzzi 1993, Lautsch 2002, Bidwell et al. 2013). However, using contractors may affect other organizational outcomes besides the intended goals. Accordingly, to understand the net effect of using contractors, strategic human capital literature has encouraged examining the effect of using contractors on important organizational outcomes (Barley et al. 2017).

In this paper, I examine how using contractors affects organizational learning, focusing on knowledge transfer between full-time employees and contractors. On the one hand, full-time employees and contractors transferring their knowledge to each other can benefit organizational learning. Contractors can transfer diverse knowledge accessed from their other affiliated organizations to the focal organization, thus facilitating organizational learning (Rosenkopf and Almeida 2003, Jain 2016, Kolympiris et al. 2019, Stadler et al. 2022). At the same time, contractors' knowledge gained from other organizations could be ineffective in the focal organization unless combined with knowledge specific to the focal firm (e.g., Huckman and Pisano 2006, Groysberg et al. 2008). Full-time employees generally possess greater firm-specific knowledge—such as the knowledge of coworkers' skills—than contractors who split time across multiple organizations and tend to have shorter employment duration.[11] Thus, full-time employees transferring their firm-specific knowledge to contractors can facilitate organizational learning by helping contractors' diverse knowledge to be more applicable to the focal firm.

Despite this potential, full-time employees and contractors may fail to transfer their knowledge to each other effectively. Employment arrangements are salient demographic characteristics that can create employee subgroups (Broschak and Davis-Blake 2006). Exacerbating the subgroup distinction, full-time employees and contractors tend to receive different levels of pay; contractors in knowledge-intensive industries tend to receive higher pay than full-time employees (Katz and Krueger 2019, DiGregorio 2022). Full-time employees and contractors in these subgroups may have poor relationships due to this in-group and out-group distinction (Tajfel and Turner 1985, Ashforth and Mael 1989). For example, full-time employees may isolate contractors in social settings due to stereotypes toward them (Kanter 1977) or behave negatively toward contractors due to perceived inequity and threats arising from the pay gap (Colquitt et al. 2013). Since a poor relationship between a knowledge source and a recipient is a major barrier to knowledge transfer (Szulanski 1996), full-time employees and contractors may not transfer knowledge to each other. If so, organizations may fail to realize the learning potential of using contractors.

Considering both benefits and challenges of using contractors, I draw from theories of majority-minority relations to argue that organizational learning depends on the proportion of contractors. These theories note that the relative sizes of subgroups affect the relationships between the subgroup members (Tolbert et al. 1999, Hewstone et al. 2012), which subsequently affects knowledge transfer between them (Argote 2013, Szulanski and Lee 2020). Theories predict both positive (Allport 1954, Blau 1977, Kanter 1977, Pettigrew and Tropp 2006, Dovidio et al. 2017) and negative effects (Blalock 1967, Allmendinger and Hackman 1995, Broschak and Davis-Blake 2006) of increasing the proportion of contractors on the relationships between the two. Specifically, increasing the proportion of contractors can improve the

[11] While some full-time employees (e.g., new hires) may have less firm-specific knowledge than contractors, I theorize that this assumption will hold *on average* due to the reasons mentioned. Indeed, in my sample, contracting physicians worked for a significantly shorter number of quarters in a hospital and treated significantly fewer patients at a hospital per quarter, on average, than full-time physicians. I also empirically control employees' firm-specific experiences.

relationship by reducing full-time employees' tendency to stereotype contractors, but it may also hurt their relationship as full-time employees aim to protect their interests from the growing size of contractors.

To reconcile these theories, I predict a non-monotonic, inverted-U relationship between organizations' proportion of contractors and learning, such that learning will peak when organizations have a moderate proportion of contractors. Initially, the positive effect of increasing the size of contractors is expected to outweigh the negative effect, improving the relationships between full-time employees and contractors. However, a further increase is expected to harm their relationships as the negative effect eventually outweighs the positive (e.g., Zatzick et al. 2003). Since positive relationships between contractors and full-time employees facilitate knowledge transfer (Szulanski 1996), organizational learning is most effective when organizations have a moderate proportion of contractors.

I test my hypothesis in the context in which the American Heart Association (AHA) and the American College of Cardiology (ACC) released a new best practice guideline in 2006 (Smith et al. 2006). This guideline recommended abandoning coronary stents in favor of medicine to treat low-severity stable coronary artery disease patients because an expensive and invasive stent was not found to be better than medicine for these patients. Organizations' adoption of the best practice indicates organizational learning in this context. This context is well-suited to examine when and how using contractors facilitates organizational learning—best practice adoption—because physicians work as either full-time employees at one hospital or contractors across multiple hospitals (Huckman and Pisano 2006, KC and Tushe 2021). The number of contractors is not trivial; 40% of physicians reported working at multiple hospitals from 2002 to 2004 (Fisher et al. 2007).

However, adopting the best practice is not simple. Medical practices persist despite research and guidelines demonstrating that the practices are unnecessary for patients, contributing to substantial waste in healthcare spending (Howard and Shen 2011). This could be due to several factors. Physicians might find the research in support of the best practices to be insufficient and require stronger evidence to change practices (Tucker et al. 2007). Patients might prefer an established treatment rather than a new best practice (Scott and Elshaug 2013). Hospitals and physicians might not be motivated to adopt the new best practice if the switch is associated with abandoning procedures central to their missions and specialties (Howard and Shen 2011, Greenwood et al. 2017). Finally, hospitals and physicians might lack knowledge of adopting the new best practice, such as whether the new best practice will likely benefit individual patients with various clinical conditions (Scott and Elshaug 2013, Greenwood et al. 2019). Among these factors, this study focuses on how using contractors can facilitate organizations' best practice adoption by promoting hospitals' and physicians' access to and creating of knowledge of adopting the new best practice.[12]

The best practice adoption in this context could be facilitated by possessing both diverse knowledge and firm-specific knowledge, which could be achieved by effective knowledge transfer between full-time employees and contractors. First, having diverse knowledge from multiple hospitals could help physicians be aware of and generate knowledge on implementing the best practice. Since the guideline was widely disseminated through various important channels (e.g., top journal publications), many physicians knew "what" the best practice was. However, the guideline only covered generalized clinical scenarios. Accordingly, physicians had to create or access additional knowledge on whether a specific patient satisfies the criteria mentioned in the new guideline and hence would benefit from medicine instead of stents. Since patients have various clinical conditions, even if they fall under the same category of "low-severity SCAD patients," the treatment decision is a complex process that requires extensive knowledge and expertise of physicians. Illustrating this complexity, a supplementary guideline released in 2009 (two years after my sample period) listed "180" common patient condition scenarios that can help physicians decide whether to use medicine for low-severity SCAD patients (Patel et al. 2009). Physicians tend to prefer action (e.g., performing stents) over inaction (e.g., not performing stents in favor of medicine) to treat patients and are generally reluctant to forgo established practices (Scott and Elshaug 2013). Thus, physicians will continue

[12] In other words, I focus on organizations' *ability to learn* and create knowledge to implement new best practices, which can be improved by an effective knowledge transfer between full-time employees and contractors. In this context, the best practice guideline was considered to be reliable and trustworthy as American Heart Association and the American College of Cardiology released the guideline. Also, organizations generally had an equal *opportunity to learn* about the best practice because the guideline was widely disseminated. As mentioned, organizations or individuals in organizations could have had different *motivations to learn* and adopt the new best practices. In my empirical analyses, I address this by controlling for various factors that may affect the motivation to adopt the best practice. Finally, I also control for factors that can affect patients' preferences toward certain procedures.

using stents unless they are confident that the patients are subject to the new guideline and can benefit from the medicine.[13] Consistent with this tendency, a study showed that stents were overused on SCAD patients, and only 50% of stents performed on SCAD patients were appropriate (Chan et al. 2011). Different hospitals are likely to possess nonredundant knowledge developed through treating different types of patients using different routines. Accessing this diverse knowledge in other hospitals can help physicians gain knowledge on identifying patients subject to the new guideline, facilitating hospitals' adoption of best practices.

Second, firm-specific knowledge is also needed to facilitate adopting the new best practice in the focal hospital. While physicians eventually make the treatment decision, physicians' interactions with other staff affect the new practice implementation processes (Greenwood et al. 2019). For example, implementing a new practice is more successful when physicians communicate the change with other staff in advance (Nilsen et al. 2020). Physicians lacking firm-specific knowledge might not know with whom to communicate the change, such as physicians and nurses receptive to the change or how to communicate effectively. Furthermore, physicians may need to coordinate with physicians from other departments to decide on the best treatment options for the patients (Howard and Shen 2011). Physicians who lack knowledge of these physicians (e.g., who have appropriate experience treating this type of patient, who are willing to help, etc.) may find it difficult to coordinate with them. As illustrated from these examples, firm-specific knowledge is necessary for hospitals to facilitate the adoption of best practices.

Using fine-grained data on 85,567 patients treated by 1,763 physicians in 40 New York state hospitals from 2004 to 2007, I find support for my hypothesis that hospitals with a *moderate* proportion of contractors adopt the new practice the most quickly. In addition, I test my theorized mechanisms by showing that organizations with a *low* or *high* proportion of contractors can improve their learning by having more contractors who can mitigate their knowledge transfer barriers. Specifically, increasing the proportion of contractors working in other organizations specialized in the new practice facilitates adoption the most at organizations with a *low* proportion of contractors because the perceived usefulness of the contractors'

[13] Thus, even if a physician adopts the new best practice for some patients, they might not use it for other patients if they lack knowledge on whether the patients (based on their clinical conditions) will benefit from the new best practice.

knowledge mitigates full-time employees' tendency to stereotype contractors. Also, having more contractors with a high workload facilitates the adoption the most at organizations with a *high* proportion of contractors because contractors' higher workload can justify their higher pay and alleviate full-time employees' perceived threats and inequity rising from the pay gap between them and contractors.

This research makes several significant contributions. First, this study contributes to the research on knowledge transfer via employee mobility by shedding light on the conditions that facilitate knowledge transfer when employees move across organizations (Mawdsley and Somaya 2016, Argote et al. 2022). Employee mobility literature has implicitly assumed that a recipient firm effectively integrates knowledge transferred by individuals that move across firms. Some research has questioned this assumption (Singh and Agrawal 2011) and encouraged future studies to examine when this assumption holds (Slavova et al. 2016). This study follows this call to directly examine when the transfer of knowledge between and individuals who move and employees of the recipient firm would be the most effective. Second, this research contributes to the microfoundations of organizational learning literature by examining how the interaction between individuals with distinct knowledge affects organizational learning (Felin et al. 2012, Argote 2013). Importantly, this study shows that the quality of this interaction depends on the relative sizes of subgroups created based on salient individual characteristics, employment arrangements. Lastly, this study contributes to strategic human capital literature by increasing understanding of the effect of employing contingent workers on important organizational outcomes (Barley et al. 2017, Ray et al. 2022).

## 3.2 Theory and Hypothesis

### 3.2.1 Employing Contractors

Organizations often employ contractors concurrently with full-time employees (Bidwell et al. 2013, Katz and Krueger 2019). Contractors have been used in many industries, such as construction, manufacturing, and entertainment. This paper specifically focuses on high-skilled contractors who work in knowledge-intensive professions, such as physicians (Huckman and Pisano 2006), information technology workers (Bidwell and Briscoe 2009), and managers (Anderson and Bidwell 2019). Many of these contractors work alongside full-time employees and perform the same tasks, but they have arms' length employment relationships with organizations (Bidwell et al. 2013, Barley et al. 2017, Katz and Krueger 2019). Naturally, they often perform the same tasks simultaneously at multiple organizations (Huckman and Pisano 2006, KC and Tushe 2021). Organizations mainly employ contractors to gain flexibility when demands fluctuate or to access specialized skills temporarily (Davis-Blake and Uzzi 1993, Lautsch 2002). Using contractors, however, may affect organizational processes and outcomes other than the main goals organizations attempt to fulfill. Thus, examining how using contractors affects various organizational outcomes is important to have a more holistic understanding of its effect on firms (Barley et al. 2017). This paper advances this understanding by investigating how employing contractors affects organizational learning. In the subsequent sections, I draw from organizational learning literature to theorize the potential benefits and challenges of using contractors in facilitating organizational learning. Then, considering both benefits and challenges, I theorize "when" using contractors can benefit learning.

### 3.2.2 How Employing Contractors Affects Organizational Learning: Benefits and Challenges

Organizational learning has been defined as "a change in the organization's knowledge that occurs as a function of experience" (Argote 2013, p.31). Learning research has frequently captured "a change in the organization's knowledge" by tracking an organization's practice changes (Levitt and March 1988). An organization's knowledge can change based on its own experience or others' experience. The latter process is referred to as knowledge transfer. Knowledge transfer can facilitate new knowledge creation as organizations integrate the transferred knowledge with their own knowledge (Miller et al. 2007). Employee mobility—the movement of individuals across organizations—is an important mechanism through which knowledge transfer occurs (Argote et al. 2022). Effective organizational learning and knowledge transfer can be a source of organizations' competitive advantage (e.g., Argote and Ingram 2000). In this regard, it is important to understand how contractors—individuals who often move across multiple organizations—transfer knowledge and affect organizational learning, manifested as a change in organizations' practices.

Research on employee mobility suggests that contractors can transfer diverse knowledge from their other affiliated firms to the focal firm. Several studies have found that individuals import knowledge when they move from one organization or team to another (Rosenkopf and Almeida 2003, Jain 2016, Kolympiris et al. 2019, Stadler et al. 2022). Individuals are powerful mechanisms through which knowledge transfers because they can transfer diverse forms of knowledge and capital, such as tacit knowledge, explicit knowledge, and relational capital (Argote and Ingram 2000, Mawdsley and Somaya 2016). Accordingly, because contractors often simultaneously work across multiple organizations, they can bring diverse knowledge from other organizations to the focal organization.

The diverse knowledge transferred by contractors can facilitate organizational learning. Research on employee mobility has noted that hiring individuals enabled organizations to create new knowledge by using knowledge shared by individuals who moved. For example, in the context of the semiconductor industry, Boeker (1997) found that hiring new top-management team members was positively associated with a firm's new product market entry based on new hires' prior experience and knowledge of different product markets. Similarly, Song et al. (2003) showed that a firm's innovation in patentable knowledge increased when the firm hired engineers who had knowledge technically distant from the firm's knowledge base. Finally, Stadler et al. (2022) showed that the mobility of engineers across different geographic units in an oil company reduced the firm's well drilling costs significantly as engineers transferred new knowledge that helped implement an innovative drilling technology. These studies indicate that contractors can facilitate knowledge creation and organizational learning in the focal organization by transferring diverse knowledge from their other affiliated organizations to the focal organization.

Despite the potential benefits of using contractors, organizational learning literature also suggests several challenges in realizing their full learning potential. First, diverse knowledge transferred by contractors might only be valuable if the focal firm effectively integrates it with the knowledge specific to the focal firm, such as the understanding of their coworkers. Several studies found that individuals' performance did not perfectly transfer or even decreased when they switched firms (Huckman and Pisano 2006, Groysberg et al. 2008). These studies suggested that the extent of knowledge transfer depended on whether the individuals who moved had well-developed knowledge specific to the focal firm. Full-time employees tend to have greater firm-specific knowledge than contractors because they typically have longer employment durations and regularly participate in employee-only events (Lautsch 2002). Hence, one way of maximizing the learning utility of contractors' diverse knowledge is for full-time employees to transfer their firm-specific knowledge to contractors and make contractors' knowledge more applicable to the firm.

However, contractors and full-time employees may not be willing to transfer knowledge to each other. Research finds that employment arrangements are salient characteristics that can create employee subgroups (Broschak and Davis-Blake 2006). Social identity theories indicate that the presence of these subgroups can lead to conflicts and competition between them (Tajfel and Turner 1985, Ashforth and Mael 1989). Notably, the knowledge transfer literature notes that this poor relationship between the knowledge source and recipient is a key barrier to knowledge transfer (see Argote 2013 and Szulanski and Lee 2020 for reviews). Individuals will not be motivated to invest time and effort to share their knowledge with others in arduous relationships (Szulanski 1996). Even if the knowledge is shared, individuals might not use it because they tend to reject knowledge shared by out-groups (Katz and Allen 1982). Furthermore, individuals will not seek knowledge from others with whom they have poor relationships to avoid elevating their coworkers' status by using their knowledge (Menon and Pfeffer 2003). These studies suggest that full-time employees and contractors might create subgroups with poor relationships and might not be motivated to transfer knowledge to each other.

As employing contractors can both benefit and limit the extent of organizational learning, it would be important to understand "when" using contractors can facilitate organizational learning. Specifically, the theories mentioned above suggest that the learning benefits of using contractors will be maximized when contractors transfer their diverse knowledge to full-time employees and full-time employees transfer their firm-specific knowledge to contractors. Furthermore, this knowledge transfer process will be effective when full-time employees and contractors have positive relationships. Thus, examining when the interaction between the full-time employee and contractor subgroups would be more positive would shed light on when using contractors can facilitate organizational learning.

Research on majority-minority relations suggests that the proportion of contractors in an organization affects the quality of interaction between full-time employees and contractors, hence the effectiveness of knowledge transfer between the two. In the next section, I theorize how the proportion of contractors in an organization affects organizational learning, focusing on its effect on the interaction quality and knowledge transfer between full-time employees and contractors.

### 3.2.3 The Relationship Between the Proportion of Contractors and Organizational Learning

Studies on majority-minority relations have theorized and found that the relative sizes of minority (i.e., contractors) and majority (i.e., full-time employees) subgroups in a unit are important determinants of the interaction quality across subgroups. These studies predict opposing effects of increasing the proportion of contractors on the relationship between contractors and full-time employees.

On the one hand, social contact theories suggest that increasing the proportion of contractors will improve the relationship between full-time employees and contractors (Allport 1954, Blau 1977, Kanter 1977, Pettigrew and Tropp 2006, Binder et al. 2009, Dovidio et al. 2017). When the proportion of contractors is low, full-time employees are likely to stereotype contractors for being different. For example, in healthcare, contracting physicians are often stereotyped as not being qualified enough to land a full-time job (Blau 2017). As the proportion of contractors increases, however, a natural increase in contact between full-time employees and contractors allows full-time employees to realize contractors' characteristics beyond the stereotypes toward them and thereby alleviate their tendency to stereotype and socially isolate contractors. As a result, the relationship between the two will improve.

On the other hand, group threat theories propose that increasing the proportion of contractors will harm the relationship between the two (Blalock 1967, Allmendinger and Hackman 1995, Broschak and Davis-Blake 2006, Outten et al. 2012). These theories suggest that individuals aim to protect their ingroup's interests. Thus, the increasing size of contractors (i.e., outgroup) heightens full-time employees' concerns that contractors may impede advancing their interests. This threat is especially likely because contractors and full-time employees tend to receive different pay levels. Katz and Krueger (2019) found that contractors received a higher hourly wage than traditional employees, even after controlling for individual characteristics and occupations. The pay gap is also prevalent in healthcare. For example, contracting nurses and physicians tend to receive higher pay than their full-time counterparts performing similar duties (Blau 2017). Also, hospitals are more willing to use expensive contractors and incur short-term expenses rather than raising full-time employees' salaries associated with long-term expenses (DiGregorio 2022). Since individuals care whether they receive a fair amount of rewards compared to their peers performing similar tasks (Adams 1965, Shaw 2014), full-time employees will perceive the pay gap between them and contractors as a serious invasion of their interests. Accordingly, full-time employees will experience negative emotions such as anger and anxiety and will behave negatively toward contractors, such as reducing helping behaviors towards them (Colquitt et al. 2013). In turn, increasing the proportion of contractors is predicted to decrease the relationship between the two.

Considering both the positive and negative effects of increasing the size of contractors, I theorize a non-monotonic, inverted-U relationship between the proportion of contractors and the interaction quality between full-time employees and contractors. Specifically, as suggested by social contact theories, the benefits of increasing the proportion of contractors at the lower level may outweigh the negative effects and improve the relationship between the two. However, as group threat theories suggest, further increasing the proportion of contractors will eventually decrease their relationship quality. This prediction is consistent with the findings from prior research. For example, Zatzick et al. (2003) also found that the likelihood of turnover for racial minority members was the lowest when an organization had a moderate proportion of them, attributing this to the lowest conflict between racial majorities and minorities.

Accordingly, I predict a non-monotonic, inverted-U relationship between the proportion of contractors and organizational learning such that knowledge transfer between the two, and thus organizational learning, is most effective when organizations have a moderate proportion of contractors. As the knowledge transfer literature suggests, full-time employees and contractors will be motivated to share their knowledge and utilize the shared knowledge if they have positive relationships. For organizations with a low or high proportion of contractors, the poor relationship between full-time employees and contractors, whether due to stereotyping or perceived threats to the group's interests, will limit the extent of knowledge transfer. Because organizational learning will be the most effective when employees have both diverse knowledge and firm-specific knowledge, as theorized above, organizational learning will be the most effective when organizations have a moderate proportion of contractors.

In my empirical context, whether organizations adopt an industry's new best practice reflects organizational learning. Based on effective knowledge transfer between full-time employees and contractors, employees in organizations with a moderate proportion of contractors will possess both diverse knowledge and firm-specific knowledge needed for the adoption. Thus, they can adopt the new best practice readily. However, for organizations with a low or high proportion of contractors, employees will lack either firm-specific knowledge or diverse knowledge. Needless to say, employees can generate knowledge they lack without accessing it from others (Greenwood et al. 2019). For example, contractors can develop firm-specific knowledge over time by performing tasks at the focal firm. Full-time employees can learn to implement the new practice through trial and error. Nonetheless, accessing the well-developed knowledge held by other employees would be faster than developing the knowledge from scratch. Thus, adopting new best practices would be the quickest on average in organizations with a moderate proportion of contractors.

**Hypothesis 1 (H1).** *Organizations with a moderate proportion of contractors will adopt industry new best practices more quickly than organizations with a low or high proportion of contractors.*

#### 3.2.4 The Moderating Effect of Contractors who Work in Other Organizations Specializing in the New Practice

While I have argued that knowledge transfer between full-time employees and contractors will not be effective in organizations with a low or high proportion of contractors, different characteristics of contractors may moderate this relationship. Contractors vary widely in their characteristics, such as other organizations they are working in or workload at the focal organization. Recall that I theorized that full-time employees *stereotyping* contractors would be the main knowledge transfer barrier in organizations with a *low* proportion of contractors. Moreover, full-time employees feeling *threats of losing their interests* will be the primary barrier in organizations with a *high* proportion of contractors. If my theorized mechanisms are in place, having more contractors that can help overcome the specific knowledge transfer barrier at an organization will facilitate the new best practice adoption the most at the organization facing the barrier. Namely, having more contractors that can help overcome the *stereotyping barrier* will improve the adoption rate *the most* in organizations with a *low* proportion of contractors. Similarly, having more contractors that can help overcome the *threats barrier* will facilitate adoption *the most* in organizations with a *high* proportion of contractors. Following this logic, I test my theorized mechanisms in this section by examining the effects of having more contractors with characteristics that can help organizations with a low or high proportion of contractors overcome their knowledge transfer barriers. Specifically, I examine (1) contractors who work in other organizations specializing in the new best practice (Hypothesis 2) and (2) contractors with a high workload at the focal organization (Hypothesis 3).

First, contractors who also work for other organizations specializing in the new best practice are likely to be perceived to have knowledge useful to implement the new best practice. For example, in my empirical context in which the new best practice was to abandon stents, some hospitals were already treating patients without using stents even before the guideline release because they did not obtain a separate license to administer stents.[14] Thus, physicians would have perceived contractors concurrently working at these hospitals to have the knowledge useful for implementing the new best practice.

Full-time employees can easily recognize the merit of using knowledge held by contractors who also work for other organizations specializing in the new best practice—the contractors' knowledge can help full-time employees implement the new best practice more quickly. Importantly, research finds that individuals do not need a high-quality relationship to transfer knowledge when the knowledge's merit is visible. Kane (2010) found that individuals needed high-quality relationships to transfer knowledge only if the merit of knowledge was not visible, as multiple interactions were needed to recognize the benefit of using others' knowledge. When it was easy to recognize the merits of knowledge, knowledge recipients used others' knowledge, despite not sharing a social identity with knowledge sharers. Hansen and Levine (2009) also found that while incumbents are generally reluctant to use newcomers' knowledge, incumbents were more likely to use newcomers' knowledge when they could easily recognize the value of newcomers' knowledge than when they could not.

[14] In my data, hospitals with and without the license to perform stents did not differ significantly in key characteristics that are likely to be associated with hospitals' quality or status, including patients' risk-adjusted length of stays, the number of quarterly patient admissions, the number of health maintenance organization contracts (i.e., a proxy of care quality), the likelihood of being a teaching hospitals and government hospitals, and the number of hospitals' beds.

While all organizations can potentially facilitate adoption by having more contractors who work in other organizations specializing in the new best practice, I predict that the benefit will be *the greatest* for organizations with a *low* proportion of contractors. I theorized that full-time employees stereotyping contractors is the main knowledge transfer barrier in organizations with a low proportion of contractors. Because full-time employees can more easily recognize the merit of knowledge held by contractors working in other organizations specializing in the practice, they will be more willing to use these contractors' knowledge and stereotype them less. This will subsequently improve their relationships, knowledge transfer, and learning in organizations with a low proportion of contractors. On the other hand, in organizations with a high proportion of contractors, full-time employees would not want to elevate contractors' status further to secure their own interests. Accordingly, they will devalue contractors' knowledge and avoid using it (Menon and Pfeffer 2003, Menon et al. 2006). Thus, even if contractors seem to have useful knowledge, full-time employees will not use contractors' knowledge in organizations with a high proportion of contractors. Finally, organizations with a moderate proportion of contractors transfer knowledge effectively and have less room for improvement. Thus, the improvement resulting from having more of these contractors will be smaller than in organizations with a low proportion of contractors. Overall, I hypothesize:

> **Hypothesis 2 (H2).** *When increasing the proportion of contractors who work in other organizations that specialize in the new practice, the improvement in the rate of adopting an industry's new best practices will be greater for organizations with a low proportion of contractors than for organizations with a moderate or high proportion of contractors.*

### 3.2.5 The Moderating Effect of Contractors with a High Workload at the Focal Organization

Next, I examine the moderating effect of having more contractors with a high workload at the focal organization and predict that the benefit of having more of these contractors will be the *greatest* for organizations with a *high* proportion of contractors. I theorized that in an organization with a high proportion of contractors, the pay gap between full-time employees and contractors leads full-time employees to perceive that contractors hinder their interests. At the same time, employees compare their input-to-outcome ratio to that of others when examining whether they are treated fairly (e.g., Adams 1965). Accordingly, when contractors perform many tasks at a focal organization that justify their high pay, full-time employees will likely perceive the pay gap as fair and not an invasion of their interests. In addition, in healthcare, contracting physicians taking a high workload can alleviate full-time physicians' workload and burnout (Zhu 2021). Accordingly, full-time physicians are less likely to view the pay gap as a threat in this case. Thus, when contractors take a high workload at the focal organization, the relationship between full-time employees and contractors will improve as full-time employees perceive lower threats toward their interests and behave less negatively toward contractors. This will improve the knowledge transfer between two employees and learning in organizations with a high proportion of contractors. On the other hand, regardless of the improved sense of equity, full-time employees will still hold stereotypes towards contractors in organizations with a low proportion of contractors, and the two groups will still have bad relationships.[15] Finally, again, organizations with a moderate proportion of contractors who have been effectively transferring knowledge will have less room for improvement. Thus, I hypothesize:

> **Hypothesis 3 (H3).** *When increasing the proportion of contractors with a high workload in the focal organization, the improvement in the rate of adopting an industry's new best practices will be greater for organizations with a high proportion of contractors than for organizations with a low or moderate proportion of contractors.*

### 3.3 Method

#### 3.3.1 Empirical Context, Data, and Sample

I examine my research question in the empirical context when the American Heart Association (AHA) and the American College of Cardiology (ACC) released a best practice guideline on January 3rd, 2006, recommending physicians stop stenting and use medicine instead to treat *low-severity stable coronary arterial disease (SCAD)* patients. Coronary artery disease is caused when plaque accumulates in arteries and blocks blood flow. SCAD is a milder coronary artery disease that does not involve heart attack or urgent chest pains. SCAD is further classified into low and high severity. The former experiences chest pains only after prolonged physical activity, while the latter experiences chest pains more often, even at rest. A stent procedure treats the disease by opening the artery and placing a stent in the artery to restore blood flow.

[15] Contractors with a high workload in the focal firm may have more contact with full-time employees and face less stereotyping from them. However, social contact theories that examined the relationship between *full-time* minority and majority members showed that the stereotyping persisted, suggesting that this possibility is less likely.

This context is ideal for my research for several reasons. First, physicians work as full-time employees or contractors across multiple hospitals during the quarter. The proportion of contracting physicians is not trivial; for example, 40% of physicians reported working at multiple hospitals (Fisher et al. 2007). Second, as mentioned earlier, translating the best practice guideline into clinical practices requires both diverse knowledge (e.g., identifying patients subject to the new guideline) and firm-specific knowledge (e.g., coordinating with the hospital's staff). Finally, I can directly observe whether each physician in each hospital follows the best practice. Accordingly, I can measure organizational learning by tracking hospitals' rate of adopting the new best practice over time. Thus, this setting is ideal for examining how the proportion of contractors affects organizational learning in terms of adopting an industry's new best practices, through its effect on knowledge transfer between full-time employees and contractors.

I utilize New York State community hospitals' quarterly inpatient discharge data between 2004 and 2007 (eight quarters before and after the guideline's release) retrieved from the State Inpatient Databases provided by the Agency for Healthcare Research and Quality. The data is developed through a Federal-State-Industry partnership and has been widely used by government and healthcare researchers. The data provides various patient-level information, allowing me to identify contractors who treated patients at multiple hospitals, observe whether physicians followed the best practice to treat patients, and control for various patient-level factors affecting physicians' choice of treatments.

To construct variables, I first limit my sample to 292,323 adult patients diagnosed with low-severity SCAD across all New York State community hospitals from 2004 to 2007. To test H1, I identify contracting physicians who treated low-severity SCAD patients at more than one hospital during the quarter (Huckman and Pisano 2006). I also count the number of low-severity SCAD patients per physician-hospital-quarter to test H3. To test H2, I retrieve data on hospitals not licensed to perform stents from the percutaneous coronary intervention outcomes reports by the New York State Department of Health. Finally, I use various other datasets to construct control variables, including the American Hospital Association's annual surveys, the New York State Department of Health's inpatient annual reports, and hospitals' websites.

After constructing the variables, I further limit the sample to run regressions to test hypotheses.[16] First, because I track stenting before and after the guideline release, I limit the sample to 230,104 patients admitted to 40 hospitals licensed to perform stents before and after the guideline release. Next, following prior research (Greenwood et al. 2017, 2019), I exclude patients who also had severe heart diseases because complex procedures other than stents might be needed for them. I used ICD-9 codes (International Classification of Diseases, Ninth Revision) to identify patients with low-severity SCAD, severe heart diseases, and stent treatments. Appendix A lists the detailed codes used. My final sample consists of 85,567 patient observations treated by 1,763 physicians in 40 New York State hospitals from 2004 to 2007.

### 3.3.2 Measures

**Dependent Variable.** Following the conventional approach of measuring learning as the change in organizational routines (Argote et al. 2022), I measure hospitals' learning as adopting the best practice. *Not* using stents for low-severity SCAD patients represents following the best practice. Accordingly, my dependent variable is *stent*, coded as 1 when a stent was used as a primary treatment and 0 otherwise. Hospitals that reduce the likelihood of using stents over time are learning the new best practice.

**Independent Variables.** My first set of independent variables is linear time splines, *period1* and *period2.* I use time splines instead of a pre/post dummy to allow hospitals' stenting rate change to differ before and after the guideline release. I place the knot at the 4th quarter of 2005 so that *period1* and *period2* measure the quarterly stenting rate change *before* and *after* the guideline release, respectively. Formally, when $t$ denotes a quarter ranging from 1 to 16 (2004 1Q to 2007 4Q), *period1* and *period2* are constructed as below:

$$period1 = \begin{cases} t & \text{if } t \leq 8 \\ 8 & \text{if } t > 8 \end{cases} \qquad period2 = \begin{cases} 0 & \text{if } t \leq 8 \\ t-8 & \text{if } t > 8 \end{cases}$$

To test H1, I first define *low* and *high* as dummy variables indicating hospitals with a low and high proportion of contractors. Then, I create interaction terms between (1) each time spline and *low* and (2) each time spline and *high*. I first identify contracting physicians who treated low-severity SCAD patients

[16] I create variables before constructing the regression sample to correctly identify physicians who treated patients at multiple hospitals (i.e., contractors) and the number of physicians who treated low-severity SCAD sample in a hospital.

at more than one hospital during the quarter (Huckman and Pisano 2006). Next, I compute a hospital's quarterly proportion of contractors as the number of contracting physicians divided by the total number of physicians who treated low-severity SCAD patients.[17] *Low* equals 1 if a hospital's quarterly proportion of contractors was lower quartile or below (14.3% cutoff), and 0 otherwise. Similarly, *high* equals 1 if a hospital's quarterly proportion of contractors was upper quartile or above (30% cutoff), and 0 otherwise. Hospitals with a moderate proportion of contractors (14.3 – 30%) serve as the baseline category. These cutoffs are also consistent with thresholds theorized by Kanter (1977). The coefficient of *period2* x *low* (or *period2* x *high)* indicates stenting rate changes over time after the guideline release for hospitals with a *low* (or *high*) proportion of contractors *relative* to hospitals with a *moderate* proportion of contractors.

To test H2, I construct interaction terms between each time spline and *more contractors in non-stent specializing hospitals*. Some contractors simultaneously treated low-severity SCAD patients in other hospitals specializing in non-stent treatments because the hospitals did not obtain a license to perform stents. I first compute a hospital's quarterly proportion of contractors working at other hospitals not licensed to perform stents among hospitals' total number of contractors. Then, I construct a dummy variable, *more contractors in non-stent specializing hospitals*, which equals 1 if a hospital has a median and above proportion of these contractors (37.5% cutoff) and 0 otherwise.

To test H3, I create interaction terms between each time splines and *more contractors with a high workload*. While contractors split their work across multiple hospitals, some contractors treated a substantial number of patients at a focal hospital. I classify contractors to have a high workload at the focal hospital if they were the top 50% of physicians regarding the number of low-severity SCAD patients treated at a hospital each quarter. Then, I compute the quarterly proportion of these contractors among the total number of contractors. Finally, I construct a dummy variable, *more contractors with a high workload*, coded as 1 if a hospital had a median and above proportion of these contractors (66.6% cutoff) and 0 otherwise.

**Control Variables.** I control for various characteristics that can affect the patient's likelihood of receiving

[17] I use the proportion of contractors among physicians who treat *low severity SCAD patients*, not among *all* physicians in a hospital. This is because physicians who treat the same disease are more likely to be interacting with each other.

stents. At the patient level, I first control several variables that affect patients' severity, such as *age*, *gender*, *race, Elixhauser comorbidity index* (Elixhauser et al. 1998, Moore et al. 2017), *emergency admission,* and *weekend admission* indicators. I also include patients' *insurance type* as patients' economic conditions can affect their preference toward certain procedures. At the physician level, I control whether a physician is a *contractor* during the quarter. In addition, to control for physicians' ability and motivation to adopt the new best practice and firm-specific knowledge levels, I include *physician's accumulated number of stents* and *physician's accumulated number of non-stents* used at the focal hospital and other hospitals, respectively.

At the hospital level, I control whether a hospital is a *public hospital* or a *teaching hospital* (a member of the Council of Teaching Hospitals) to control a hospital's motivation to adopt the new best practice (Greenwood et al. 2017). I also control for a hospital's *number of beds*. To control the amount of knowledge and coordination costs that affect a hospital's adoption rate (Steiner 1972), I also include a hospital's quarterly *number of physicians* who treated low-severity SCAD patients. I control *health system or network* dummy because hospitals can gain knowledge through affiliated hospitals. I include a hospital's *number of patient admissions* to capture how busy a hospital was during a quarter. I also include *number of health maintenance organization (HMO) contracts* because HMOs tend to contract more with higher-quality hospitals (Gaskin et al. 2002). At the region level, I control for the quarterly *number of stenting hospitals in the region,* as other hospitals in the same referral region could affect a hospital's stenting decision. Table 3.1 reports the variables' descriptive statistics. Appendix B displays the correlation matrix.

– Insert Table 3.1 about here –

### 3.3.3 Econometric Models

While this study examines the variation in learning at the *organizational level*, I conduct analysis at the *patient level* consistent with prior studies that examined the healthcare context (Huckman and Pisano 2006, KC et al. 2013, Greenwood et al. 2017, 2019). This enables controlling for important patient-level characteristics that affect patients' likelihood of receiving stents. As my dependent variable is a dummy *stent*, I test my hypotheses using linear probability models. Equation (1) shows the model for testing H1:

$$P(Stent_{ipht} = 1) = \beta_0 + \beta_1 period1_t + \beta_2 period2_t + \beta_3 low_{ht} + \beta_4 high_{ht} \\ + \beta_5 period1_t \times low_{ht} + \beta_6 period1_t \times high_{ht} \\ + \beta_7 period2_t \times low_{ht} + \beta_8 period2_t \times high_{ht} \\ + \beta_9 \boldsymbol{X} + \delta_p + \delta_h + u_{ipht} \tag{1}$$

Subscripts *i*, *p*, *h*, and, *t* indicate patient, physician, hospital, and quarter. ***X*** is a vector of controls. I include physician ($\delta_p$) and hospital fixed effects ($\delta_h$) and cluster standard errors by hospital and quarter. A greater negative coefficient of *period2* indicates abandoning stents more quickly after the guideline release. Hence, *positive* and significant coefficients of *period2* x *low* ($\beta_7$) and *period2* x *high* ($\beta_8$) indicate that hospitals with low and high proportions of contractors abandon stents more slowly than hospitals with moderate proportions of contractors, supporting H1. Importantly, I examine the adoption rate over time instead of the time until the first adoption because the adoption might not continue if the first adoption was symbolic or if the adoption subsequently dampens (Naumovska et al. 2021).

To test H2 and H3, I conduct subgroup analyses based on hospitals' proportion of contractors (low vs. moderate vs. high) and compare coefficients from each subgroup analysis using seemingly unrelated regressions (e.g., Doshi et al. 2013). Equation (2) shows the model for each subgroup to test H2 and H3:

$$P(Stent_{ipht} = 1) = \beta_0 + \beta_1 period1_t + \beta_2 period2_t \\ + \beta_3 period1_t \times more\ contractors\ in\ nonstent\ hosp_{ht} + \beta_4 period2_t \times more\ contractors\ in\ nonstent\ hosp_{ht} \\ + \beta_5 period1_t \times more\ contractors\ w.high\ workload_{ht} + \beta_6 period2_t \times more\ contractors\ w.high\ workload_{ht} \\ + \beta_7 more\ contractors\ in\ nonstent\ hosp_{ht} + \beta_8 more\ contractors\ w.high\ workload_{ht} + \beta_9 \boldsymbol{X} + \delta_p + \delta_h + u_{ipht} \tag{2}$$

H2 predicts that *more contractors in non-stent specializing hospitals* will facilitate abandoning stents *the most* for organizations with a *low* proportion of contractors. Thus, H2 will be supported if the coefficient of *period2* x *more contractors in non-stent specializing hospitals* ($\beta_4$) is significantly more negative for hospitals with a *low* proportion of contractors than others. H3 predicts that *more contractors with a high workload* will facilitate *the most* abandonment for organizations with a *high* proportion of contractors. Therefore, H3 will be supported if the coefficient of *period2* x *more contractors with a high workload* ($\beta_6$) is significantly more negative for hospitals with a *high* proportion of contractors than others.

**3.4 Results**

Table 3.2 shows the results of the regression analyses that test H1. Model 1 includes the control variables only. Results suggest that patients who are female, with more comorbidities, and admitted on weekends are less likely to receive stents than others ($p < 0.01$). Busy hospitals with more quarterly patients are associated with a higher likelihood of stenting ($p < 0.05$). Model 2 adds independent variables without interactions.

– Insert Table 3.2 about here –

To test H1, in model 3 of Table 3.2, I include interactions between each time spline and *low* (and *high*). Both coefficients for *period2 x low* and *period 2 x high* are positive and significant, supporting H1 that hospitals with a low or high proportion of contractors abandon stents more slowly than hospitals with a moderate proportion of contractors ($p < 0.05$). Based on the regression results, Figure 3.1 depicts the total new best practice adoption rate (stent abandonment rate) for each type of hospital. For hospitals with a moderate proportion of contractors, the likelihood of using stents decreases by 7.2 percentage points over the eight quarters after the guideline release. Contrarily, the predicted likelihood of using stents does not change significantly after the guideline release for hospitals with a low and high proportion of contractors.

– Insert Figure 3.1 about here –

To test H2 and H3, I examine the interactions between each time spline and *more contractors in non-stent specializing hospitals* (H2) and the interactions between each time spline and *more contractors with a high workload* (H3). This is done for each subgroup based on hospitals' proportion of contractors (low, moderate, high). As explained above, H2 will be supported if the coefficient of *period2* x *more contractors in non-stent specializing hospitals* of hospitals with a *low* proportion of contractors is significantly more negative than those of other hospitals. Similarly, H3 will be supported if the coefficient of *period2* x *more contractors with a high workload* of hospitals with a *high* proportion of contractors is significantly more negative than those of other hospitals. Table 3.3 models 1-3 show the results to test H2 only; models 4-6 show the results to test H3 only; models 7-9 show the results of the full model with all interactions. As results are consistent across models, I interpret the results based on models 7-9.

– Insert Table 3.3 about here –

For H2, the coefficient of *period2* x *more contractors in non-stent specializing hospitals* for hospitals with a *low* proportion of contractors is negative and significant in Table 3.3 model 7 ($p < 0.01$), showing that having more of these contractors facilitated abandoning stents in these hospitals. Models 8-9 show that coefficients of *period2* x *more contractors in non-stent specializing hospitals* are statistically indistinguishable from zero for other hospitals; having more of these contractors didn't facilitate the abandonment in these hospitals. Based on Wald tests, the coefficient of *period2* x *more contractors in non-stent specialized hospitals* for hospitals with a *low* proportion of contractors is significantly more negative than that of hospitals with *moderate* ($p < 0.01$) and *high* ($p < 0.05$) proportion of contractors. Figure 3.2, plotted based on these results, shows that the adoption rate *improvement* when hospitals have *more contractors in non-stent specializing hospitals* is greatest for hospitals with a *low* proportion of contractors. These results support H2 that having more contractors that work in other organizations specializing in the new best practice improves the adoption rate the most for organizations with a low proportion of contractors.

– Insert Figure 3.2 about here –

For H3, the coefficient of *period2* x *more contractors with a high workload* with a high proportion of contractors is negative and significant in Table 3.3 model 9 ($p < 0.05$). Having more of these contractors facilitated abandoning stents for hospitals with a *high* proportion of contractors. For other hospitals, Models 7 and 8 show that having more of these contractors did not significantly affect hospitals' stent abandoning trend. Wald test results find that the coefficient of *period2* x *more contractors with a high workload* for hospitals with a *high* proportion of contractors is significantly more negative than that for other hospitals ($p < 0.1$). Based on these results, Figure 3.3 also depicts that the adoption rate *improvement* is largest for hospitals with a *high* proportion of contractors when having *more contractors with a high workload*. These results support H3 that having more contractors with a high workload at the focal organization facilitates the new best practice adoption the most for organizations with a high proportion of contractors.

– Insert Figure 3.3 about here –

### 3.4.1 Robustness Checks

I first retest H1 using a continuous measure of the proportion of contractors and find robust support for H1. I also retest H1 by using an alternative operationalization of contractors. While my operationalization of contractors as employees working across multiple organizations during the period is consistent with the approach by prior studies (e.g., Huckman and Pisano 2006, Greenwood et al. 2019), it has two limitations. Specifically, full-time employees may have worked in multiple hospitals in the same health system, and contractors may have worked in only one hospital during the quarter. To address these limitations, I alternatively measure contractors as physicians who worked in multiple hospitals not in the same health system for more than 50% of the quarters during our sample period. H1 is robust to this alternative measure. Appendix C discusses these results in detail. Finally, H2 and H3 are reexamined and supported using three-way interaction terms on the full sample. I explain these results in Appendix D.

### 3.5 Additional Analyses

#### 3.5.1 Do Both Full-time Employees and Contractors Adopt the Best Practice in Organizations with a Moderate Proportion of Contractors?

I theorized that knowledge transfer between full-time employees and contractors would be effective in organizations with a moderate proportion of contractors. If so, both full-time employees and contractors in organizations with a moderate proportion of contractors will adopt the new best practice after the guideline release. This is because they will possess both diverse and firm-specific knowledge needed to adopt the new best practice through effective knowledge transfer. Contrarily, employees in organizations with a low or high proportion of contractors might not adopt the best practice after the guideline release because they lack either diverse or firm-specific knowledge due to ineffective knowledge transfer. To test this, I split my sample into six based on hospitals' proportion of contractors (low, moderate, high) and whether physicians were full-time employees or contractors. Then, I ran linear probability models including all control variables on each subgroup. Consistent with my theory, results in Table 3.4 show that both types of employees in hospitals with a moderate proportion of contractors adopted the best practice after the guideline release, evidenced by the negative and significant coefficients of p*eriod2* in model 2 ($p < 0.1$) and model 5 ($p < 0.05$). However, the coefficients of *period2* for both employees in hospitals with a low and high proportion of contractors were insignificant. These results corroborate my argument that knowledge transfer between the two employees is effective only in organizations with a moderate proportion of contractors.

– Insert Table 3.4 about here –

### 3.5.2 Is a Higher Firm-specific Knowledge of Contractors an Alternative Mechanism for H3?

H3 predicted that having more contractors with a high workload at the focal organization will facilitate the best practice adoption the most in organizations with a high proportion of contractors. This is because full-time employees will perceive the pay gap between full-time employees and contractors to be reasonable and are less likely to feel threats to their groups' interests. Alternatively, organizations' adoption rate might have improved as contractors with a high workload at the focal organization accumulate more firm-specific knowledge. Since these contractors possess both diverse and firm-specific knowledge, in organizations with a high proportion of contractors, contractors' best practice adoption could have facilitated organizations' practice adoption even without effective knowledge transfer between full-time employees and contractors.

If this were the alternative mechanism, full-time employees would not be adopting the best practice in organizations with a high proportion of contractors because they lack diverse knowledge due to ineffective knowledge transfer. To examine this, I ran linear probability models to test the interaction between *period2* and *more contractors with a high workload* including all control variables on two subsamples, full-time employees vs. contractors in organizations with a high proportion of contractors. The coefficients of *period2 x more contractors with a high workload* in Table 3.5 models 1 and 2 are negative and significant ($p < 0.05$), showing that both full-time employees and contractors in hospitals with a high proportion of contractors adopted the best practice. Hence, while contractors with a high workload in the focal organization could have accumulated more firm-specific knowledge, I do not find evidence that this is the sole alternative mechanism driving the results of H3.

– Insert Table 3.5 about here –

## 3.6 Discussion and Conclusion

This research examines how using contractors affects organizational learning in terms of organizations' adoption of an industry's new best practices. Unfortunately, our understanding of how contractors affect important organizational processes, such as learning, has not kept pace with the prevalence of contractors in the workforce (Barley et al. 2017). Also, while contractors can potentially transfer knowledge from one organization to another, the transfer process could be challenging. Hence, I ask when using contractors facilitates organizational learning by examining when transferring knowledge between full-time employees and contractors would be the most effective, a process often neglected in the employee mobility literature.

The knowledge transfer literature suggests that the effectiveness of knowledge transfer depends on the interaction quality between full-time employees and contractors. At the same time, full-time employees and contractors are likely to create subgroups (Broschak and Davis-Blake 2006), and their relative sizes are important determinants of the relationships across subgroups (Blalock 1967, Kanter 1977). Accordingly, I examine how the proportion of contractors in an organization affects knowledge transfer and organizational learning. Considering both positive effects (i.e., better interaction quality through more social integration) and negative effects (i.e., worse interaction quality to preserve self-interests) of increasing the proportion of contractors on knowledge transfer, I theorize that organizational learning will peak when organizations have a moderate proportion of contractors. Using fine-grained data on 85,567 patients treated by 1,763 physicians in 40 New York state hospitals from 2004 to 2007, I find that hospitals with a moderate proportion of contractors indeed learned the industry's new best practices the fastest after the AHA and the ACC recommended that physicians stop using stents for low-severity SCAD patients.

Moreover, organizations with a low or high proportion of contractors can facilitate the adoption by using specific types of contractors who can help mitigate the organizations' knowledge transfer barriers. Specifically, organizations with a low proportion of contractors can facilitate adoption by having more contractors working in other organizations specializing in the new best practice, as the perceived usefulness of these contractors' knowledge mitigates full-time employees' tendency to stereotype contractors. Organizations with a high proportion of contractors can facilitate adoption by having more contractors with a high workload at the focal organization because full-time employees are less likely to perceive these contractors' higher pay as an invasion of their self-interests. These findings provide important support to my theorized mechanisms and practical guidance for organizations to overcome knowledge transfer barriers when they need to maintain a low or high proportion of contractors due to their unique needs.

These findings have several implications. First, this study contributes to the research on knowledge transfer via employee mobility and microfoundations of organizational learning. (Felin et al. 2012, Argote et al. 2022). Many employee mobility studies have assumed that firms effectively integrate knowledge transferred via employee mobility. Scholars urged future research to examine this assumption directly and identify when the knowledge brought through employee mobility becomes firm-level knowledge versus continues to reside in individuals who moved (Mawdsley and Somaya 2016). This study takes the microfoundational approach and suggests that the validity of this assumption depends on the relative size of the subgroups created based on employee characteristics. Future studies could examine these findings in other employee mobility cases with different employee characteristics that can create subgroups in firms.

These results also shed light on the research on strategic human capital (Ray et al. 2022) and organizational design that leads to the development of dynamic capabilities (Teece et al. 1997). My results show how the composition of human capital resources in terms of the size of contractors affects organizational learning, an important yet understudied topic given the prevalence of contingent workers (Bidwell et al. 2013, Barley et al. 2017). By examining organizations' industry new best practice adoption, this study also responds to the call of the strategic human capital literature to examine behavioral outcomes more proximate than performance (Ray et al. 2022). My results also suggest that organizations' ability to maintain a moderate level of contractors in their workforce can be a source of dynamic capabilities that facilitates updating organizational practices. This suggests that organizational design factors, such as their hybrid workforce management systems, can contribute to competitive advantage in changing environments.

This study also contributes to the healthcare industry. The COVID-19 pandemic has exacerbated hospitals' workforce shortages. One approach to addressing this challenge has been to hire contractors. However, this study suggests that having too many contractors can deteriorate relationship dynamics among workers, hurting knowledge transfer and care coordination between them. Furthermore, social comparison between subgroups can trigger other negative consequences. For instance, hospitals report incidents of full-time employees leaving and joining the same hospital again as contractors due to their pay discrepancy, exacerbating hospitals' costs (Criscione 2021). Hence, this study encourages hospitals to carefully consider multidimensional effects of using contractors and decide the optimal size of contractors in their workforce.

This study is not without limitations, providing opportunities for future research. First, this study shares the challenges of other studies that examined contractors; that is, the specifics of employments vary widely across industries, firms, and individuals. Accordingly, this study's theories and findings might not be generalizable to other contractors with different characteristics. This study examined high-skilled contractors working alongside full-time employees performing the same tasks. Many contractors (e.g., IT workers and managers) examined by prior research share these characteristics. However, some contractors might perform lower-skilled tasks and receive lower pay than full-time employees. This skill or status difference might be confounded with the relative sizes of contractors and full-time employees in an organization and further complicate the knowledge transfer process. Future studies could further validate this study's findings in different empirical contexts. Relatedly, this study does not distinguish between independent contractors and contractors hired by agencies as the data is not available. These contractors may create further subgroups based on whether they are hired by agencies or which agencies they belong to. Future studies could use more fine-grained data to examine how the co-existence of different types of contractors affects knowledge transfer dynamics in organizations. Lastly, omitted variables may affect both organizations' likelihood of hiring contractors and their speed of adopting new best practices. The non-monotonic, inverted-U nature of my results mitigates some of these concerns. Also, I address this limitation by including relevant control variables, conducting additional analyses, and accompanying several news articles and research from my empirical context that qualitatively support my theoretical arguments.

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### 3.8 Tables and Figures

**Table 3.1** Descriptive Statistics

| Variables | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| ***Patient-level (85,567 patient observations)*** | | | | |
| Stent | 0.70 | 0.46 | 0.00 | 1.00 |
| Patient age | 65.79 | 11.49 | 25.00 | 100.00 |
| Patient female | 0.33 | 0.47 | 0.00 | 1.000 |
| Patient comorbidity index | 6.49 | 9.25 | -4.00 | 74.00 |
| Patient weekend admission | 0.05 | 0.22 | 0.00 | 1.00 |
| Patient race[a] | | | | |
| White | 0.63 | | | |
| Black | 0.09 | | | |
| Hispanic | 0.08 | | | |
| Asian or Pacific Islander | 0.02 | | | |
| Native American | 0.01 | | | |
| Other | 0.08 | | | |
| Unknown | 0.09 | | | |
| Patient insurance type[a] | | | | |
| Medicare | 0.54 | | | |
| Medicaid | 0.10 | | | |
| Private insurance | 0.33 | | | |
| Self-pay | 0.01 | | | |
| No charge | 0.001 | | | |
| Other | 0.01 | | | |
| Patient emergency admission[a] | | | | |
| Emergency | 0.39 | | | |
| Non-emergency | 0.60 | | | |
| Unknown | 0.01 | | | |
| ***Physician-level (10,790 physician-quarter observations)*** | | | | |
| Contractor | 0.25 | 0.43 | 0.00 | 1.00 |
| ***Physician-hospital level (11,700 physician-hospital-quarter observations)*** | | | | |
| Physician's accum. no. of stents at focal hosp. | 84.20 | 179.75 | 0.00 | 3101.00 |
| Physician's accum. no. of non-stents at focal hosp. | 15.47 | 58.70 | 0.00 | 915.00 |
| Physician's accum. no. of stents at other hosp. | 37.94 | 65.93 | 0.00 | 968.00 |
| Physician's accum. no. of non-stents at other hosp. | 11.31 | 36.56 | 0.00 | 763.00 |
| ***Hospital-level (635 hospital-quarter observations)*** | | | | |
| Low | 0.26 | 0.44 | 0.00 | 1.00 |
| High | 0.25 | 0.44 | 0.00 | 1.00 |
| More contractors in non-stent hospitals | 0.52 | 0.50 | 0.00 | 1.00 |
| More contractors with high workload | 0.51 | 0.50 | 0.00 | 1.00 |
| Public hospital | 0.18 | 0.38 | 0.00 | 1.00 |
| Teaching hospital | 0.68 | 0.47 | 0.00 | 1.00 |
| No. of beds | 766.84 | 459.95 | 180.00 | 2242.00 |
| No. of physicians | 35.96 | 15.71 | 5.00 | 87.00 |
| Health system or network | 0.79 | 0.41 | 0.00 | 1.00 |
| No. of admissions | 6689.00 | 2920.02 | 1913.00 | 14147.00 |
| No. of HMO contracts | 11.97 | 9.24 | 0.00 | 35.00 |
| ***Region-level (172 region-quarter observations)*** | | | | |
| No. of hospitals in region | 3.97 | 3.60 | 1.00 | 13.00 |

*Note*: [a] The proportion of observations in each category is reported for these variables.

**Table 3.2** Linear Probability Model Regression Estimates for the Likelihood of Administering Stents (H1)

| **DEPENDENT VARIABLE: Stent** | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| **INDEPENDENT VARIABLES** | | | |
| Period1 | | 0.003 | 0.004 |
| | | (0.003) | (0.003) |
| **Period2** | | **-0.003** | **-0.009**$^{**}$ |
| | | **(0.003)** | **(0.003)** |
| Low | | 0.005 | 0.005 |
| | | (0.010) | (0.029) |
| High | | 0.005 | -0.018 |
| | | (0.011) | (0.029) |
| Period1 x Low | | | -0.004 |
| | | | (0.005) |
| Period1 x High | | | 0.001 |
| | | | (0.004) |
| **Period2 x Low (H1)** | | | **0.012**$^{*}$ |
| | | | **(0.005)** |
| **Period2 x High (H1)** | | | **0.010**$^{*}$ |
| | | | **(0.004)** |
| More contractors in non-stent hospitals | | 0.001 | 0.002 |
| | | (0.009) | (0.010) |
| More contractors with high workload | | 0.019$^{*}$ | -0.019$^{*}$ |
| | | (0.009) | (0.009) |
| **CONTROL VARIABLES** | | | |
| Patient age | -0.0003 | -0.0002 | -0.0002 |
| | (0.0002) | (0.0003) | (0.0003) |
| Patient female | -0.044$^{**}$ | -0.044$^{**}$ | -0.044$^{**}$ |
| | (0.006) | (0.006) | (0.006) |
| Patient comorbidity index | -0.005$^{**}$ | -0.005$^{**}$ | -0.005$^{**}$ |
| | (0.0004) | (0.0004) | (0.0004) |
| Patient weekend admission | -0.170$^{**}$ | -0.170$^{**}$ | -0.170$^{**}$ |
| | (0.018) | (0.018) | (0.018) |
| Contractor | -0.003 | -0.004 | -0.003 |
| | (0.008) | (0.008) | (0.008) |
| Physician’s accum. no. of stents at focal hosp. | -0.00002 | -0.00001 | -0.00001 |
| | (0.00002) | (0.00002) | (0.00002) |
| Physician’s accum. no. of non-stents at focal hosp. | 0.0002 | 0.0002 | 0.0002 |
| | (0.0002) | (0.0002) | (0.0002) |
| Physician’s accum. no. of stents at other hosp. | -0.00002 | -0.000004 | -0.00002 |
| | (0.00004) | (0.00005) | (0.0001) |
| Physician’s accum. no. of non-stents at other hosp. | 0.0002 | 0.0003 | 0.0003 |
| | (0.0002) | (0.0002) | (0.0002) |
| Public hospital | 0.004 | 0.004 | 0.008 |
| | (0.019) | (0.020) | (0.021) |
| Teaching hospital | -0.004 | -0.001 | -0.002 |
| | (0.023) | (0.021) | (0.021) |
| No. of beds | -0.00001 | -0.000001 | -0.000003 |
| | (0.0001) | (0.0001) | (0.0001) |
| No. of physicians | 0.0002 | 0.0003 | 0.0003 |
| | (0.0007) | (0.001) | (0.001) |
| Health system or network | -0.021 | -0.023 | -0.015 |
| | (0.016) | (0.020) | (0.025) |
| No. of admissions | 0.00004$^{*}$ | 0.00004$^{*}$ | 0.00004$^{**}$ |
| | (0.00002) | (0.00001) | (0.00001) |
| No. of HMO contracts | -0.003 | -0.003 | -0.003 |
| | (0.003) | (0.003) | (0.002) |
| No. of hospitals in region | 0.005 | 0.006 | 0.007 |
| | (0.007) | (0.007) | (0.006) |
| Hospital and physician FEs | Yes | Yes | Yes |
| Observations | 85,567 | 85,567 | 85,567 |
| Number of Hospitals | 40 | 40 | 40 |

*Notes*: Standard errors clustered by hospital and quarter are reported in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$. Results for the patient race, insurance type, and emergency admission indicators are not displayed in the interest of space.

**Table 3.3** Linear Probability Model Regression Estimates for the Likelihood of Administering Stents: Subgroup Analyses based on Hospitals' Proportion of Contractors (H2-H3)

| **DEPENDENT VARIABLE: Stent** | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 |
|---|---|---|---|---|---|---|---|---|---|
| *Hospitals' proportion of contractors* | *low* | *moderate* | *high* | *low* | *moderate* | *high* | *low* | *moderate* | *high* |
| Period1 | -0.010 | 0.009 | 0.001 | 0.006 | 0.005 | -0.001 | -0.008 | 0.010 | 0.0005 |
| | (0.009) | (0.005) | (0.005) | (0.013) | (0.006) | (0.003) | (0.014) | (0.007) | (0.005) |
| Period2 | 0.012$^{**}$ | -0.009$^{*}$ | -0.001 | -0.005 | -0.011 | 0.004 | 0.007 | -0.013 | 0.003 |
| | (0.004) | (0.004) | (0.004) | (0.010) | (0.008) | (0.004) | (0.009) | (0.008) | (0.005) |
| More contractors in non-stent hospitals | -0.048$^{*}$ | 0.038 | -0.010 | 0.029 | -0.003 | -0.035 | -0.047$^{*}$ | 0.034 | -0.015 |
| | (0.023) | (0.048) | (0.054) | (0.018) | (0.014) | (0.033) | (0.024) | (0.047) | (0.055) |
| More contractors with high workload | 0.009 | 0.019 | 0.026 | 0.035 | 0.020 | 0.040 | 0.017 | 0.024 | 0.043 |
| | (0.015) | (0.017) | (0.024) | (0.037) | (0.040) | (0.039) | (0.037) | (0.041) | (0.039) |
| Period1 x More contractors in non-stent hospitals | 0.020$^{**}$ | -0.007 | -0.002 | | | | 0.019$^{**}$ | -0.007 | -0.003 |
| | (0.006) | (0.008) | (0.007) | | | | (0.007) | (0.008) | (0.007) |
| **Period2 x More contractors in non-stent hospitals (H2)** | **-0.022$^{**}$** | **0.004** | **-0.001** | | | | **-0.021$^{**}$** | **0.004** | **0.002** |
| | **(0.007)** | **(0.005)** | **(0.006)** | | | | **(0.008)** | **(0.005)** | **(0.005)** |
| Period1 x More contractors with high workload | | | | -0.006 | -0.002 | 0.003 | -0.003 | -0.002 | 0.003 |
| | | | | (0.008) | (0.009) | (0.007) | (0.008) | (0.009) | (0.007) |
| **Period2 x More contractors with high workload (H3)** | | | | **0.011** | **0.005** | **-0.015$^{*}$** | **0.006** | **0.005** | **-0.015$^{*}$** |
| | | | | **(0.008)** | **(0.008)** | **(0.007)** | **(0.008)** | **(0.008)** | **(0.007)** |
| Constant | 0.055 | 0.459$^{**}$ | 0.456$^{\dagger}$ | 0.040 | 0.465$^{*}$ | 0.573$^{**}$ | 0.029 | 0.435$^{*}$ | 0.581$^{**}$ |
| | (0.277) | (0.176) | (0.254) | (0.278) | (0.192) | (0.221) | (0.286) | (0.177) | (0.219) |
| **Wald test $\chi^2$ statistic (vs. *low*) (H2)** | | **8.08$^{**}$** | **5.49$^{*}$** | | | | | **6.80$^{**}$** | **6.24$^{*}$** |
| **Wald test $\chi^2$ statistic (vs. *high*) (H3)** | | | | **2.97$^{\dagger}$** | **5.40$^{*}$** | | **2.99$^{\dagger}$** | **3.68$^{\dagger}$** | |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hospital and Physician FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 27,177 | 43,374 | 15,016 | 27,177 | 43,374 | 15,016 | 27,177 | 43,374 | 15,016 |
| Number of Hospitals | 28 | 38 | 25 | 28 | 38 | 25 | 28 | 38 | 25 |

*Note*: Standard errors clustered by hospital and quarter are reported in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$.

**Table 3.4** Additional Analysis: Linear Probability Model Regression Estimates for the Likelihood of Administering Stents: Subgroup Analyses based on Hospitals' Proportion of Contractors (low, moderate, high) and Physicians' Employment Arrangements (full-time, contractors)

| **DEPENDENT VARIABLE: Stent** | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| *Employment type* | | *Full-time employees* | | | *Contractors* | |
| *Hospitals' proportion of contractors* | *low* | *moderate* | *high* | *low* | *moderate* | *high* |
| Period2 | 0.001 | -0.007$^{\dagger}$ | -0.002 | 0.002 | -0.007$^{*}$ | 0.0003 |
| | (0.005) | (0.005) | (0.007) | (0.008) | (0.003) | (0.004) |
| Independent and control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Hospital and Physician Fes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21,997 | 27,472 | 5,836 | 5,180 | 15,902 | 9,180 |
| Number of Hospitals | 28 | 38 | 25 | 27 | 37 | 25 |

*Notes*: Standard errors clustered by hospital and quarter are reported in parentheses. In Model 4, the number of hospitals is 27 because one hospital in the category did not have any contractors throughout the sample period. In Model 5, the number of hospitals is 37 because all patients of one hospital in the category had an indicator of severe heart disease and were excluded from the regression sample based on the sample exclusion criteria. $^{*}p < 0.05$, $^{\dagger}p < 0.10$.

**Table 3.5** Additional Analysis: Linear Probability Model Regression Estimates for the Likelihood of Administering Stents: Subgroup Analyses for Hospitals with a High Proportion of Contractors Only, based on Physicians' Employment Arrangements (full-time, contractors)

| **DEPENDENT VARIABLE: Stent** | Model 1 | Model 2 |
|---|---|---|
| *Employment type* | *Full-time employees* | *Contractors* |
| Period2 | 0.008 | 0.002 |
| | (0.005) | (0.004) |
| More contractors with high workload | 0.028 | 0.051 |
| | (0.039) | (0.044) |
| **Period2 x More contractors with high workload** | **-0.023**$^{*}$ | **-0.011**$^{*}$ |
| | **(0.008)** | **(0.005)** |
| Independent and control variables | Yes | Yes |
| Hospital and Physician Fes | Yes | Yes |
| Observations | 5,836 | 9,180 |
| Number of Hospitals | 25 | 25 |

*Notes*: Standard errors clustered by hospital and quarter are reported in parentheses. $^{*}p < 0.05$. A parallel set of variables constructed for *Period1* are also included but are not displayed in the interest of spa

**Figure 3.1** Hospitals' Predicted Total Decrease in the Likelihood of Administering Stents Across Eight Quarters After the Guideline Release for Hospitals with a *Low* vs. *Moderate* vs. *High* proportion of Contractors (H1)

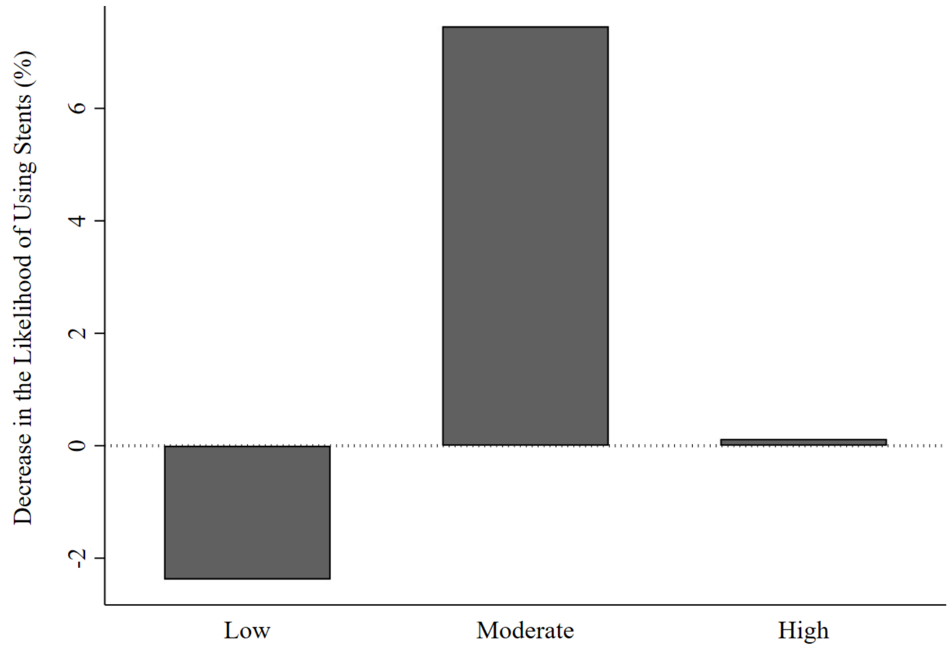



**Figure 3.2** Hospitals' Predicted Total Decrease in the Likelihood of Administering Stents Across Eight Quarters After the Guideline Release for Hospitals with a *Low* vs. *Moderate* vs. *High* proportion of Contractors based on *More Contractors in Non-stent Hospitals* levels (H2)

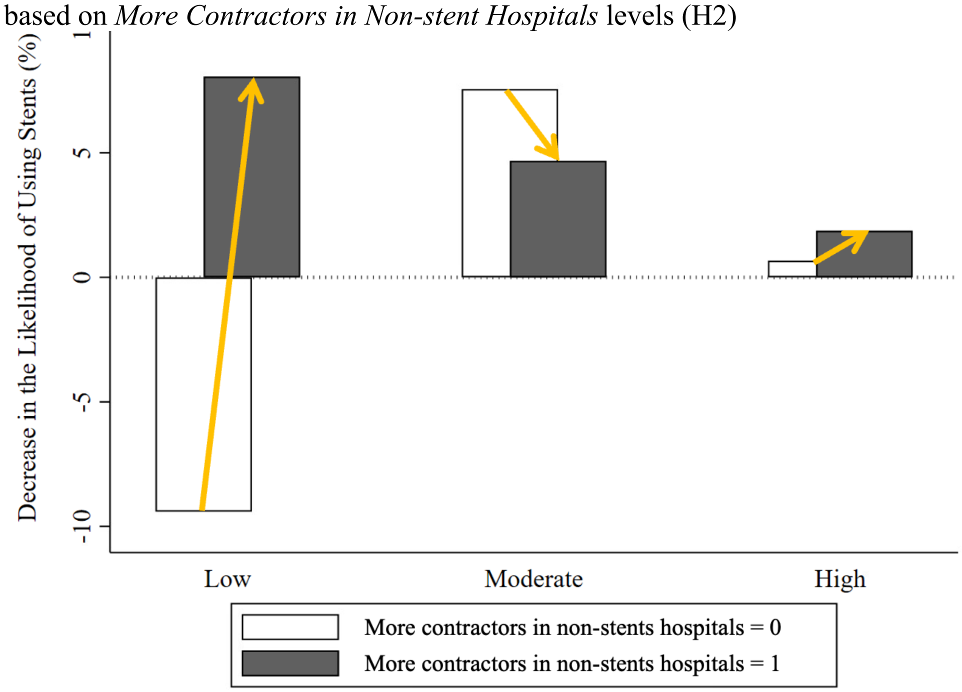
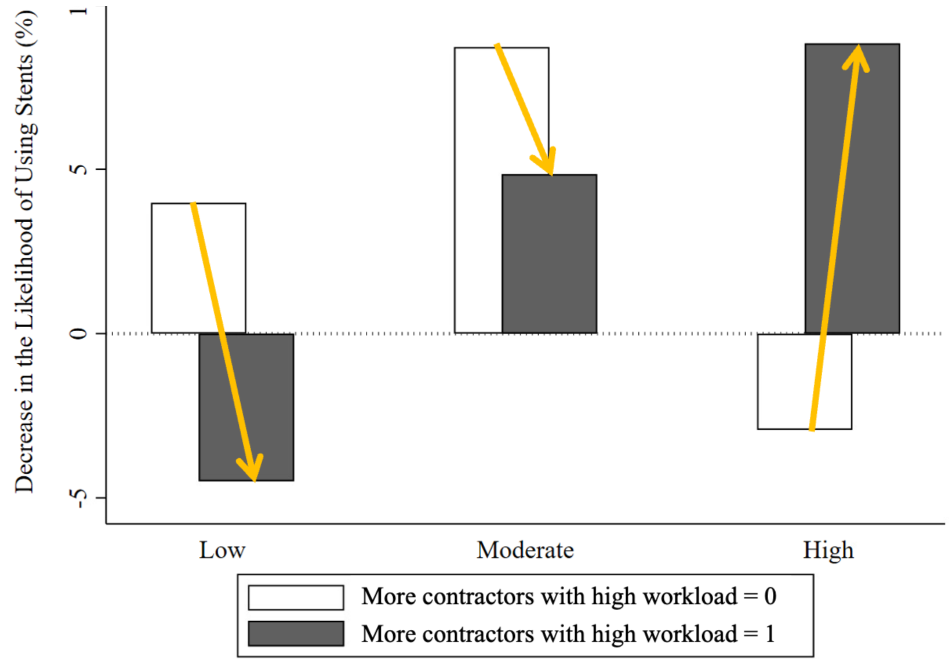


**Figure 3.3** Hospitals' Predicted Total Decrease in the Likelihood of Administering Stents Across Eight Quarters After the Guideline Release for Hospitals with a *Low* vs. *Moderate* vs. *High* proportion of Contractors based on *More Contractors with high workload* levels (H3)



## 3.9 Appendices

### Appendix A

Consistent with the medical literature, I used ICD-9 codes (i.e., International Classification of Diseases, Ninth Revision) to identify patients with low-severity stable coronary artery disease (SCAD), severe heart diseases (acute coronary syndrome, coronary artery bypass graft, high-severity SCAD), and stent treatments. Heart diseases are classified into two broad subcategories—SCAD and acute coronary syndrome (Berry 2017). Following the medical literature's approach (Jackevicius et al. 2002, Mohan et al. 2014), I identified SCAD patients as heart disease patients with no diagnosis of acute coronary syndromes.

In addition, following the new best practice guideline (Smith et al. 2006), the low-severity vs. high-severity SCAD distinction was made based on the Canadian Cardiovascular Society angina classification (Campeau 1976). Specifically, low-severity SCAD patients' symptoms fall under Grades I and II, in which chest pains do not limit ordinary physical activity significantly. On the other hand, high-severity SCAD patients' symptoms fall under Grades III and IV, in which chest pains limit ordinary physical activity and may be present even at rest. Accordingly, I read each ICD-9 code description to classify SCAD patients into low and high severities. Notably, the descriptions of codes 413.0 (chest pain that occurs during sleep), 413.1 (chest pain that mostly arises when a person is at rest), and 413.9 (includes chest pains of Grades III and IV) satisfied the description of Grades III and IV classifications. Thus, I classified patients with these ICD-9 codes as high-severity SCAD patients and the rest of the SCAD patients as low-severity SCAD patients. Table A lists the ICD-9 codes used to identify each patient category.

**Table A. List of ICD-9 Codes Used to Identify Patients' Diagnoses and Procedures**

| Diagnosis/Procedure | ICD-9 codes | References |
|---|---|---|
| Stent | 00.66, 36.01, 36.02, 36.05, 36.06, 36.07, 36.09[a] | Kim et al. 2014, Mohan et al. 2014 |
| Acute coronary syndrome (Heart attack & Unstable angina) | 410 – 411 | Jackevicius et al. 2002, Bertoni et al. 2005 |
| Coronary artery bypass graft | 36.10 – 36.19 | Sollano et al. 1999, Ricciardi et al. 2008 |
| Low-severity SCAD | 412, 414 | See descriptions above |
| High-severity SCAD | 413.0, 413.1, 413.9 | See descriptions above |

*Note.* [a] Code 00.66 replaced codes 36.01, 36.02, and 36.05 effective October 2005.

## Appendix B

**Table B. Correlation Matrix (*n*=85,567)**

| | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Stent | | | | | | | | | | | | | |
| 2 | Period1 | 0.02 | | | | | | | | | | | | |
| 3 | Period2 | -0.003 | 0.58 | | | | | | | | | | | |
| 4 | Low | -0.001 | -0.11 | -0.02 | | | | | | | | | | |
| 5 | High | -0.03 | 0.09 | 0.04 | -0.31 | | | | | | | | | |
| 6 | More contractors in non-stent hospitals | 0.04 | -0.25 | -0.23 | 0.07 | -0.12 | | | | | | | | |
| 7 | More contractors with high workload | 0.05 | 0.07 | 0.09 | 0.14 | -0.10 | -0.08 | | | | | | | |
| 8 | Patient age | -0.02 | 0.02 | 0.02 | 0.01 | 0.01 | -0.04 | -0.01 | | | | | | |
| 9 | Patient female | -0.07 | -0.01 | -0.001 | -0.01 | 0.002 | 0.01 | 0.01 | 0.15 | | | | | |
| 10 | Patient race | 0.02 | -0.08 | -0.07 | 0.13 | -0.08 | -0.01 | 0.13 | -0.08 | 0.02 | | | | |
| 11 | Patient comorbidity index | -0.20 | 0.06 | 0.06 | -0.01 | -0.01 | -0.04 | 0.04 | 0.09 | 0.08 | 0.01 | | | |
| 12 | Patient insurance type | 0.03 | -0.02 | -0.01 | -0.01 | 0.005 | 0.03 | -0.02 | -0.60 | -0.15 | 0.03 | -0.15 | | |
| 13 | Patient emergency admission | 0.23 | 0.04 | 0.05 | 0.05 | -0.01 | 0.09 | 0.12 | 0.02 | -0.04 | 0.02 | -0.04 | -0.02 | |
| 14 | Patient weekend admission | -0.18 | -0.01 | -0.005 | 0.01 | -0.01 | -0.004 | -0.003 | 0.001 | 0.03 | -0.01 | 0.08 | -0.02 | -0.17 |
| 15 | Contractor | 0.10 | 0.03 | 0.01 | -0.23 | 0.25 | -0.02 | 0.04 | -0.02 | 0.01 | 0.02 | -0.04 | 0.01 | 0.02 |
| 16 | Physician’s accum. no. stents at focal hosp. | 0.19 | 0.34 | 0.32 | -0.02 | -0.04 | -0.18 | 0.08 | 0.04 | -0.02 | -0.06 | -0.03 | -0.02 | 0.07 |
| 17 | Physician’s accum. no. non-stents at focal hosp. | 0.01 | 0.30 | 0.27 | 0.07 | -0.08 | -0.24 | 0.03 | 0.03 | -0.01 | 0.01 | 0.02 | -0.02 | 0.01 |
| 18 | Physician’s accum. no. stents at other hosp. | 0.07 | 0.15 | 0.16 | -0.10 | 0.16 | -0.12 | 0.06 | -0.01 | 0.003 | 0.05 | -0.03 | 0.002 | -0.002 |
| 19 | Physician’s accum. no. non-stents at other hosp. | 0.09 | 0.16 | 0.16 | -0.13 | 0.16 | -0.11 | 0.04 | -0.02 | 0.01 | 0.04 | -0.02 | 0.01 | 0.04 |
| 20 | Public hospital | -0.04 | 0.001 | 0.02 | -0.14 | -0.03 | 0.17 | -0.14 | -0.05 | 0.02 | -0.05 | 0.02 | 0.05 | -0.08 |
| 21 | Teaching hospital | 0.01 | -0.02 | 0.004 | 0.03 | -0.10 | -0.07 | 0.24 | -0.05 | 0.03 | 0.21 | 0.03 | 0.02 | 0.07 |
| 22 | No. of beds | 0.004 | 0.08 | 0.08 | 0.25 | -0.17 | -0.15 | 0.29 | -0.01 | -0.004 | 0.08 | 0.03 | -0.004 | 0.03 |
| 23 | No. of physicians | 0.02 | 0.04 | 0.01 | 0.25 | -0.16 | -0.09 | -0.05 | 0.01 | -0.01 | 0.10 | -0.01 | -0.01 | 0.03 |
| 24 | Health system or network | 0.08 | 0.12 | 0.06 | -0.11 | 0.13 | -0.13 | 0.16 | 0.02 | -0.01 | -0.06 | -0.02 | -0.02 | 0.01 |
| 25 | No. of admissions | 0.001 | 0.09 | 0.08 | 0.23 | -0.13 | -0.26 | 0.24 | 0.02 | -0.01 | 0.15 | 0.04 | -0.03 | 0.13 |
| 26 | No. of HMO contracts | 0.05 | 0.03 | 0.06 | 0.26 | -0.28 | 0.10 | 0.07 | -0.02 | 0.01 | 0.22 | -0.02 | 0.02 | -0.03 |
| 27 | No. hospitals in region | 0.04 | 0.11 | 0.10 | 0.23 | -0.10 | -0.18 | 0.23 | -0.01 | 0.01 | 0.23 | 0.03 | -0.02 | 0.08 |

**Table B. Correlation Matrix (*n*=85,567) (Continued)**

| | Variables (Continued) | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 15 | Contractor | -0.04 | | | | | | | | | | | | |
| 16 | Physician's accum. no. stents at focal hosp. | -0.05 | -0.06 | | | | | | | | | | | |
| 17 | Physician's accum. no. non-stents at focal hosp. | -0.03 | -0.15 | 0.57 | | | | | | | | | | |
| 18 | Physician's accum. no. stents at other hosp. | -0.03 | 0.36 | 0.03 | -0.04 | | | | | | | | | |
| 19 | Physician's accum. no. non-stents at other hosp. | -0.03 | 0.42 | 0.03 | -0.06 | 0.52 | | | | | | | | |
| 20 | Public hospital | 0.02 | -0.01 | -0.11 | -0.07 | 0.02 | 0.01 | | | | | | | |
| 21 | Teaching hospital | -0.002 | 0.02 | -0.08 | 0.05 | 0.04 | 0.05 | 0.19 | | | | | | |
| 22 | No. of beds | -0.01 | -0.06 | 0.04 | 0.06 | 0.01 | 0.01 | -0.03 | 0.51 | | | | | |
| 23 | No. of physicians | 0.001 | -0.10 | 0.01 | 0.06 | -0.03 | -0.002 | -0.19 | 0.23 | 0.37 | | | | |
| 24 | Health system or network | -0.02 | 0.13 | 0.14 | -0.11 | 0.11 | 0.09 | -0.59 | -0.13 | 0.18 | 0.13 | | | |
| 25 | No. of admissions | -0.02 | -0.09 | 0.16 | 0.21 | -0.01 | 0.06 | -0.28 | 0.51 | 0.56 | 0.53 | 0.13 | | |
| 26 | No. of HMO contracts | -0.002 | -0.15 | 0.02 | 0.06 | -0.07 | -0.07 | -0.02 | 0.42 | 0.16 | 0.31 | -0.13 | 0.31 | |
| 27 | No. hospitals in region | -0.01 | -0.09 | 0.09 | 0.17 | 0.07 | 0.05 | -0.24 | 0.37 | 0.32 | 0.40 | 0.09 | 0.46 | 0.51 |

**Appendix C. Robustness Check: Retesting H1 Using a Continuous Measure of the Proportion of Contractors and an Alternative Operationalization of Contractor**

I retest H1 using a continuous measure of the proportion of contractors in organizations. To test this, I examine (1) the interaction between *period2* and *proportion of contractors* and (2) the interaction between *period2* and the *proportion of contractors squared*. I expect the single-term interaction to be negative and significant because a greater proportion of contractors initially facilitates abandoning stents as the knowledge transfer between contractors and full-time employees improves. However, the squared-term interaction will be positive and significant because a too high proportion of contractors can hurt knowledge transfer and stent abandonment. Table B model 1 results are consistent with this prediction (single-term interaction $b$ = -0.20, $p$ < 0.01; square-term interaction $b$ = 0.35, $p$ < 0.01). Based on these results, Figure B shows that the predicted total *decrease* in the likelihood of using stents after the guideline release is the highest for hospitals with a moderate proportion of contractors. Hence, H1 is again supported.

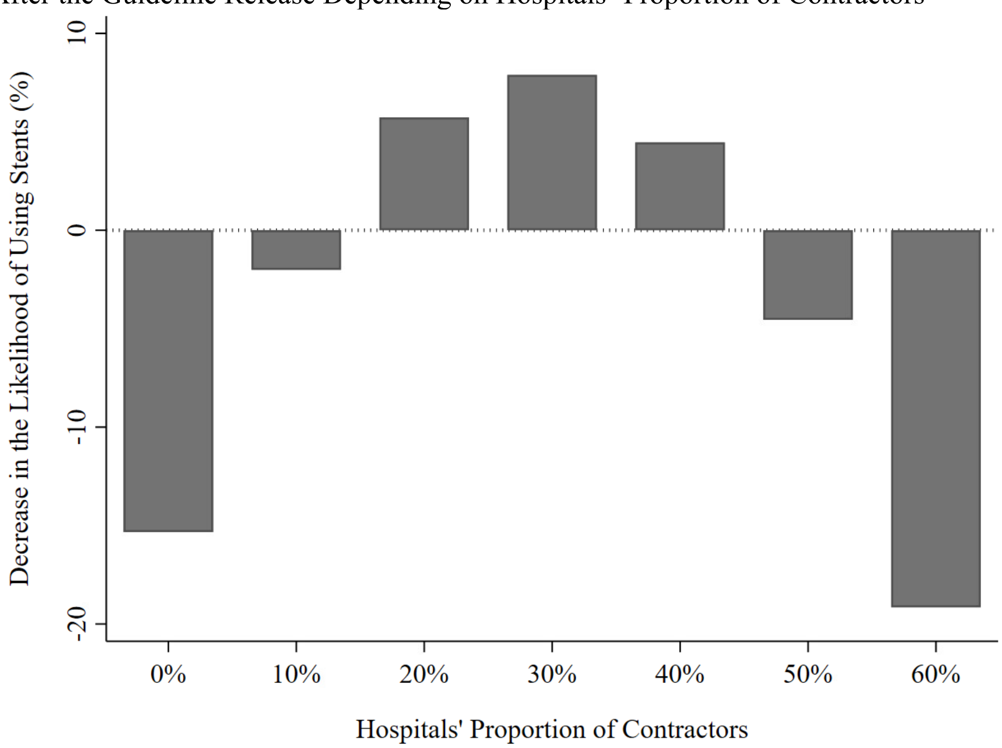
Next, I retest H1 by using an alternative operationalization of contractors. While my operationalization of contractors as employees working across multiple organizations during the period is consistent with the approach by prior studies (Huckman and Pisano 2006, Greenwood et al. 2019), it has two limitations. First, full-time physicians could have treated patients in multiple hospitals in the same health system. For example, a physician fully employed by Montefiore medical center at Moses may have treated patients at Montefiore Medical Center at Einstein if needed. As a result, this physician would have been mistakenly coded as a contractor. Second, contractors could have treated patients in only one hospital during the period, but these contractors would have been classified as full-time employees. To examine the robustness of my contractor operationalization to these limitations, I alternatively measured contractors as physicians who worked in multiple hospitals not in the same health system for more than 50% of the quarters. Then, I constructed the proportion of contractors using this more conservative measure. Finally, I retested H1 by examining the (1) interaction between *period2* and *proportion of contractors* and (2) the interaction between *period2* and the *proportion of contractors squared* as in the above. Results in Table B model 2 are consistent with those in Table B model 1 that used my original contractor operationalization (single-term interaction $b = -0.20$, $p < 0.05$; square-term interaction $b = 0.45$, $p < 0.05$). Thus, H1 was robust to this alternative measure of contractors.

**Table C.** Robustness Check: Linear Probability Model Regression Estimates for the Likelihood of Administering Stents (a) Using a Continuous Measure of the Proportion of Contractors to Test H1 (Model 1) and (b) Using an Alternative Operationalization of Contractor to Test H1 (Model 2)

| **DEPENDENT VARIABLE: Stent** | Model 1 | Model 2 |
|---|---|---|
| Period2 | 0.019* | 0.012† |
| | (0.008) | (0.007) |
| Proportion of contractors[a] | -0.250 | 0.088 |
| | (0.425) | (0.063) |
| Proportion of contractors squared[a] | -0.525 | -0.545 |
| | (0.722) | (0.533) |
| **Period2 x Proportion of contractors (H1)[a]** | **-0.201**** | **-0.198*** |
| | **(0.065)** | **(0.074)** |
| **Period2 x Proportion of contractors squared (H1)[a]** | **0.349**** | **0.448*** |
| | **(0.114)** | **(0.168)** |
| Control variables | Yes | Yes |
| Hospital and physician Fes | Yes | Yes |
| Observations | 85,567 | 85,567 |
| Number of Hospitals | 40 | 40 |

*Notes*: Standard errors clustered by hospital and quarter are reported in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$. A parallel set of variables constructed for *Period1* are also included but are not displayed in the interest of space.
[a] The results in Model 2 are based on an alternative operationalization of contractors.

**Figure C.** Hospitals' Predicted Total Decrease in the Likelihood of Administering Stents Across Eight Quarters After the Guideline Release Depending on Hospitals' Proportion of Contractors



**Appendix D. Robustness Check: Retesting H2 and H3 Using Three-way Interactions**

I reexamined H2 and H3 using three-way interaction terms on the full sample. To test H2, I included all combinations of two-way and three-way interaction terms between (1) each time spline, *more contractors in non-stent hospitals*, and *low* and (2) each time spline, *more contractors in non-stent hospitals,* and *high* to the H1 model specification. Based on H2, when organizations have more contractors who work in other organizations specializing in the new practice, the adoption rate *improvemen*t will be the greatest for organizations with a *low* proportion of contractors. The coefficient of *period 2* x ***low*** x *more contractors in non-stent hospitals* represents the degree of improvement for hospitals with a *low* proportion of contractors compared to hospitals with a *moderate* proportion of contractors. The coefficient was negative and significant ($b$ = -0.02, $p < 0.05$), showing that having more of these contractors facilitated the stent abandonment more for hospitals with a low proportion of contractors than for hospitals with a moderate proportion of contractors. Similarly, the **difference** in the coefficients of *period 2* x ***low*** x *more contractors in non-stent hospitals* and *period 2* x ***high*** x *more contractors in non-stent hospitals* indicates the degree of improvement for hospitals with a *low* proportion of contractors compared to hospitals with a *high* proportion of contractors. The difference was negative and significant ($b$ = -0.02, $p < 0.05$), again showing that the improvement was greater for hospitals with a low proportion of contractors. These results support H2.

Similarly, to test H3, I included all interaction terms across (1) each time spline, *more contractors with high workload,* and *low* and (2) each time spline, *more contractors with high workload,* and *high* to the H1 model specification. H3 predicts that when organizations have more contractors with a high workload at the focal organization, the adoption rate *improvemen*t will be the greatest for organizations with a *high* proportion of contractors. Consistent with this prediction, the improvement was greater for hospitals with a *high* proportion of contractors than hospitals with a *low* proportion of contractors (**difference** in *period 2* x ***low*** x *more contractors with high workload* and *period 2* x ***high*** x *more contractors with high workload;* $b$ = -0.02, $p < 0.05$) and than hospitals with a *moderate* proportion of contractors (*period 2* x ***high*** x *more contractors with high workload;* $b$ = -0.02, $p < 0.1$). Thus, H3 is again supported.

**Table D.** Robustness Check: Linear Probability Model Regression Estimates for the Likelihood of Administering Stents Using Three-way Interactions to Test H2 and H3

| **DEPENDENT VARIABLE: Stent** | Model 1 |
|---|---|
| Period2 x Low x More contractors in non-stent hospitals (H2) | -0.022* |
| | (0.008) |
| Period2 x High x More contractors in non-stent hospitals (H2) | -0.001 |
| | (0.007) |
| Period2 x Low x More contractors with high workload (H3) | 0.001 |
| | (0.007) |
| Period2 x High x More contractors with high workload (H3) | -0.017† |
| | (0.009) |
| Independent and control variables | Yes |
| Hospital and physician Fes | Yes |
| Observations | 85,567 |
| Number of Hospitals | 40 |

*Notes*: Standard errors clustered by hospital and quarter are reported in parentheses. *$p < 0.05$, †$p < 0.10$. A parallel set of variables constructed for *Period1,* all single-terms and two-way interaction terms are also included but are not displayed in the interest of space.

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