GOAL-RELATEDNESS AND LEARNING: EVIDENCE FROM HOSPITALS

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Abstract

Organizations vary significantly in the rates at which they learn from experience (i.e., ‘learning-by-doing’). While prior work has explored how different categories of prior experience affect learning outcomes, limited attention has been paid to the role played by the organizational context. We focus on one important aspect of an organization’s context – goals – and examine how the degree of goal-relatedness across an organization’s diverse set of activities affects the rate at which it learns from experience. In doing so, we argue that even where otherwise diverse activities are knowledge-related, if they are not goal-related, learning-by-doing is likely to suffer. Using data from the hospital industry our findings suggest that goal-relatedness is an important consideration when it comes to learning. Although goal-related teaching aids learning-by-doing in clinical care, we find that strong academic affiliations (and the research-oriented tasks and goals they bring with them) may detract from it.

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Introduction

It has long been recognized that building and sustaining competitive advantage depends crucially on an organization’s ability to learn (Stata 1989, Teece, Pisano et al. 1997, Argote 1999). Although learning is a competitive imperative, prior work finds that organizations vary significantly in their ability to do so (Argote, Beckman et al. 1990, Pisano, Bohmer et al. 2001). Given the strategic role of learning, as well as the variability that exists across organizations in how they learn, it is not surprising that both managerial practice and the academic literature have sought to understand the factors that lead to effective learning in organizations (Senge 1990, Argote 1999).

A large body of literature on organizational learning has explained this variation by looking at differences that arise from learning-by-doing (Pisano 1994, Argote and Todorova 2007). These differences include not only the amount of cumulative experience an organization accrues, but also the type of experience (Lapré and Nembhard 2010). For example, recent work has gained valuable insight by dividing experience into increasingly fine categories – e.g., customer served (Clark, Huckman et al. 2013) and firm-specificity (Huckman and Pisano 2006). Other work in this area has looked beyond the boundaries of a focal task to consider the role an organization’s other activities play (Schilling, Vidal et al. 2003, Clark and Huckman 2012). One of the key insights of this latter line of thinking has been to show that a diversity of activities and experiences may be valuable for learning. Specifically, this literature has argued that learning and performance may be enhanced by engaging simultaneously in
activities that are related in terms of the knowledge (e.g., know-what, know-how) they require (Schilling, Vidal et al. 2003, Tanriverdi and Venkatraman 2005, Clark and Huckman 2012, KC and Staats 2012).

The learning benefits of such knowledge-relatedness have been empirically observed at the individual (Narayanan, et al. 2009; Staats and Gino 2012), the group (Schilling, Vidal et al. 2003) and the operating unit (Clark and Huckman 2012) levels.

Importantly, the addition of diverse activities may introduce more than productive knowledge to an organization. More specifically, the introduction of diverse activities may impact not only the means of production (i.e., an organization’s productive capabilities), but also its ends—the purposes to which the organization aspires. Accordingly, in this paper we focus attention on goals; the purposes of an organization’s various activities and, more importantly, the performance targets those purposes impose on individuals and groups in the organization. Indeed, while diverse activities may be operationally related in terms of knowledge, we argue that where such knowledge-relatedness does not coincide with goal-relatedness (i.e., where diverse activities introduce multiple, unrelated goals), learning and performance improvement may suffer. More specifically, we argue that goal-relatedness (i.e., goal alignment) is a necessary condition enabling the kind of improvement that arises from learning complementarities across activities.¹ One of the reasons that goals have received little attention in the study of learning-by-doing may be that in order to study it effectively data must be collected on many organizations over a multiple year period. In addition, many strategic activities are not tracked in a comparable, and public way, across organizations. We consider these issues in the health care setting, where organizations (i.e., hospitals) frequently diversify beyond clinical services, bringing a variety of activities and goals into the

¹ We note here the important distinction between learning complementarities and learning spillovers. Prior research has documented the important role that knowledge spillovers can play in driving the level of productivity both within and across firms (Jaffe, Trajtenberg & Henderson, 1993; Henderson & Cockburn, 1996; Thornton & Thompson, 2001; Thompson & Fox-Kean, 2005), but such effects are distinct from the complementarities that have been the focus of the learning literature on knowledge-relatedness (Schilling, Vidal et al. 2003, Clark and Huckman 2012, KC and Staats 2012). Complementarities are present when increasing the intensity of one activity increases the rate of return to doing more of another activity. Roberts (2004) described the distinction in this way: “…complementarity is conceptually different from a positive spillover. A positive spillover occurs when the overall benefit from some activity (rather than the returns to increasing the activity) is increasing in the level of the other activity” (pg. 73). Thus, our focus in this paper is on the role that goals play in enabling (or disabling) learning complementarities across knowledge-related activities.
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organization. In the hospital industry, these additional activities can be readily observed and measured for many organizations over time. Thus, to answer our research questions we assembled a unique dataset consisting of 293,198 patients receiving percutaneous transluminal coronary angioplasty (PTCA) heart procedures in 79 New Jersey and Maryland hospitals between 2000 and 2008.

In this setting, diversification beyond clinical services comes most frequently in the form of academic affiliations. Medical schools are pluralistic organizations, where the logic of clinical care and the logic of scientific research coexist (Dunn and Jones, 2010), though the latter has long been recognized as dominant (Zuckerman, 1977; Bloom 1988; Zerhouni, 2005). We consider how such affiliations—which generate different goals and incentives, including the publish-or-perish paradigm—influence learning rates associated with PTCA clinical outcomes. By bringing together multiple data sources, we not only achieved the ability to advance the study of learning in organizations and answer our questions empirically, but we also gained valuable insight on healthcare in general (which represented 17.5% of US GDP in 2014, Center for Medicare and Medicaid Services, 2015) and cardiac care in particular (the cost of cardiovascular disease and stroke in the United States was estimated to be $315.4 billion in 2010, Go, et al., 2014).

Our study makes several important contributions to the literature. While prior scholars have pointed to the complexities multiple goals introduce to organizations (Ethiraj and Levinthal, 2009), our study is the first to consider multiple goals in the context of learning-by-doing. Specifically, our study provides empirical evidence that learning depends not only on the knowledge characteristics of a diverse set of activities and experiences, but also on the purposes of those activities.

Our findings along these lines offer four additional contributions. First, we highlight the important role that goals play in converting experience into performance. In particular, we find that learning tradeoffs may occur when organizations pursue diverse activities representing multiple, unrelated goals, even when those activities are related in terms of their knowledge content (i.e., knowledge-related). Second, we empirically document a learning-by-teaching effect. In our setting, we conceptualize teaching as an activity that is both knowledge- and goal-related to clinical care (i.e., PTCA). Such a learning-by-
teaching effect has been discussed in the literature at the individual level, but we are not aware of any
evidence of it at the level of the organization. Moreover, we are able to show that this effect is not just the
result of any human capital development activity, but rather derives from the depth and intensity of on-
the-job teaching activities. Third, our study follows calls in the literature to pursue a deeper understanding
of the context of learning (Argote and Miron-Spektor 2011). These calls have identified goals as one of
several potentially important contextual factors at the organization level. Thus, our paper’s focus on
multiple goals and goal-relatedness takes a step forward in terms of our understanding of how context
influences learning rates. Finally, our results contribute not only to the academy, but also to the practice
of healthcare, suggesting key ways that organizations can learn and deliver services more effectively.

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Learning-by-doing

The act of repeatedly doing something generally leads to learning and improvement with respect
to its performance. Indeed, that we frequently use the phrases “learning-by-doing” and “learning from
experience” interchangeably is recognition that the taking of repeated action (i.e., doing) and the accrual
of knowledge (i.e., experience) go hand in hand (Lapré and Nembhard 2010, Argote and Miron-Spektor
2011). In seeking to understand this phenomenon, we note that in general performance improvement
depends on having both a reason or desire (i.e., motivation) and the ability or means (i.e. opportunity) to
do so. One important source of motivation is the presence of a perceived gap between current
performance and aspiration levels (Cyert and March 1963, Greve 1998). Similarly, an important source of
opportunity is the prior knowledge available to those seeking improvement.

With this in mind, the act of “doing”, and the experience that comes with it, represents an
especially powerful learning mechanism, in part, because it has the potential to impact both the
motivation and the opportunity to improve performance. Experience produces both feedback (i.e.,
knowledge) about prior actions and information about current performance levels. Such knowledge and
information become crucially important to what scholars have called problemistic search (Cyert and
March 1963, Gavetti, Levinthal et al. 2007). That is, search in response to a perceived problem (Katila
and Ahuja, 2002). Triggered by problemistic search, actions associated with success are more likely to be reproduced than are actions associated with failure (March 2011). Attempting to replicate success more consistently by drawing upon feedback (i.e., knowledge from prior actions), constitutes a primary mechanism that underlies learning from experience (Starbuck et al. 2008; March 2011). Consequently, more experience allows organizations to refine feedback models, leading to more effective searches for solutions to perceived problems.

Empirical support for the “learning curve” has proven to be quite robust, both across time (Yelle 1979; Argote 1999; Lapré 2011) and across levels of analysis (Reagans, Argote and Brooks, 2005), including individuals (e.g., Newell and Rosenbloom 1981), teams (e.g., Pisano, Bohmer and Edmondson 2001), and organizations (e.g., Argote, Beckman and Epple 1990). Consistent with these empirical results, we begin with the following calibrating hypothesis:

*Hypothesis 1: The more experience an organization has with a focal task the better its performance will be with respect to that focal task*

**Multiple Goals and Learning**

Given that the availability of prior knowledge plays an important role in creating the opportunity to learn, it’s not surprising that scholars have looked to an organization’s knowledge base to explain performance differences across organizations (Ahuja and Katila, 2001; Reagans, Argote and Brooks, 2005; Tanriverdi and Venkatraman 2005). More specifically, scholars studying learning-by-doing have examined the underlying knowledge effect of diversifying the tasks and activities within individuals and organizations. For example, studies have shown that engaging in a variety of tasks and activities may be valuable for learning when those activities are related in terms of their knowledge content (Schilling, Vidal et al. 2003, Narayanan, Balasubramanian et al. 2009, Clark and Huckman 2012, Staats and Gino 2012). Yet the diversification of activities can introduce much more than new, related knowledge to the organization. For example, the addition of diverse activities may also introduce additional goals the organization wishes to pursue. The pursuit of multiple goals is an aspect of task and activity diversification that the literature on learning-by-doing has yet to consider. This oversight is surprising.
since learning-by-doing is most often manifested as performance improvement and, accordingly, the performance goals to which organizations aspire represent a natural place to look for variation in learning (Ethiraj and Levinthal 2009). In considering the learning implications of multiple goals, our fundamental argument is simple: where diverse activities introduce additional unrelated performance targets, learning-by-doing is likely to suffer, even in the presence of knowledge-relatedness. Conversely, where performance targets are aligned, knowledge-related activities will have the expected complementary effect. **Figure 1** presents a visual depiction of our theoretical framework.

We begin our consideration of the predictions presented in Figure 1 by considering the expected negative influence of tasks with unrelated goals on both the motivation and the opportunity to learn from experience. While we often consider organizations as entities constructed to pursue a single overall goal (e.g., profit maximization), the reality is that organizations often pursue multiple goals simultaneously. For example, in an effort to improve profitability, a firm may seek to increase sales growth, decrease costs, improve R&D productivity, increase customer satisfaction, and enhance product quality (among other goals). While these distinct goals appear complementary at the outset, empirical work has shown that organizational goals like these are often weakly related, or unrelated (Meyer 2002). Such goal-relatedness has important implications for learning-by-doing due to challenges that may arise at both the individual and organization level, and which may be manifest in slower rates of learning-by-doing.

**Trade-offs at the Individual Level**

At the individual level, multiple, unrelated goals can present difficult choices that may cause one goal to suffer at the expense of the other. As Ethiraj and Levinthal (2009) note, “even in simple organizations with one individual having no interdependencies with others, as one action has implications for multiple performance goals and achieving one goal starts undermining the other, the coordination problem starts to become real and trade-offs inevitable.” The problems and trade-offs become even more challenging when individuals have to choose between different activities corresponding to the multiple goals. Thus, as individuals are forced to trade off one goal for another, the marginal benefit associated
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with focal task experience may suffer. Employees faced with multiple, unrelated goals have less time for reflection after the focal task, due to the demands of other goals. Reflection represents intentional attempts to synthesize, abstract, and articulate the key lessons taught by experience; and has been found to make direct experience more productive (DiStefano, Gino et al. 2014). Such reflection is impacted by the complexity that multiple, unrelated goals introduce. More specifically, while diverse knowledge-related activities can be more easily synthesized when they contribute to a common performance target, efforts to reflect and synthesize the same activities are naturally more complicated, more fragmented, and require more effort, when those activities tie to separate, unrelated performance targets. In such a situation, employees “face an effort allocation challenge of dividing their time among the goals to be pursued” (Ethiraj and Levinthal 2009). Therefore, individuals who are forced to pursue multiple unrelated performance goals may learn less from experience due to diminished opportunities for reflection.

Multiple goals may also reduce the motivation of individuals to learn from experience in the focal task. The presence of multiple, unrelated goals may necessitate repeated cycles of “cognitive switching” i.e., costly cognitive readjustments that individuals incur as they switch from one task (goal) to another (Monsell 2003; Staats and Gino 2012). Repeated cognitive switching may prove exhausting over time. To this end, prior work has shown that individuals deal with multiple goals by focusing on only one goal (Shah, Friedman, and Kruglanski 2002), distorting both effort and attention towards goals that are more measureable (Holmstrom and Milgrom 1991; Gilliland and Landis 1992), and exhibiting heterogeneous preferences for certain organizational goals over others (Cyert and March 1963). As a result, individuals faced with multiple goals may lack motivation to reflect and engage in other cognitive processes required for “higher-level” learning with respect to the focal task (Fiol and Lyles 1985). Therefore, as organizations increase the intensity of activity associated with an unrelated goal, both the opportunity and motivation of individuals to learn may be diminished, impeding the translation of focal task experience into performance improvements.

Coordination Problems at the Organization Level

At the organization level, multiple, unrelated goals can likewise create unintended challenges to
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effective knowledge transfer and coordination. First, the goals to which an organization aspires are central to the “mindsets” of its leaders, which in turn exert an important influence on the distribution of resources within the organization (Grant 1988). For example, Prahalad and Bettis (1986) have argued that the success of diversification hinges on relatedness in terms of leader mindsets — what they termed “dominant logics” — that form the foundation of resource allocation decisions. The more mindsets leaders have to balance, the more they are forced to spread organizational resources (including their own minds) thin, leaving less time, resources, and energy for the focal task and collective learning in their domain.

Second, as previously mentioned, individuals tend to exhibit heterogeneous preferences for different goals (Cyert and March 1963). This has important implications for coordination across the organization. When focal task performance necessitates the knowledge and timely actions of several employees across the organization (Thompson 1967; Galbraith 1977; Grant 1996), a shared understanding of the meaning and purpose of the work is an important prerequisite to effective coordination (Carton, Murphy, and Clark 2014). When employees must balance multiple, unrelated goals, and possess distinct goal preferences – either due to explicit assignment, or due to individual preferences – the lack of a “shared understanding” of the purpose of work may lead to communication errors and other inconsistent actions between employees in the implementation of the focal task (Carton, Murphy, and Clark 2014). In other words, as employees interpret their experience and extract meaning in different ways (due to distinct goal preferences), their ability to act in a concerted way, to communicate openly and to share knowledge, may be hampered. Such interpersonal challenges are likely to have a demotivating effect on collective action. In addition, such coordination challenges represent learning opportunities foregone, impeding the kind of collective behavior that is necessary to improve group and organization-level processes, and learn from collective experience.

Given these expectations at both the individual and organization levels, we offer the following hypothesis concerning activities with unrelated goals:

*Hypothesis 2*: Where the goal of a knowledge-related activity is unrelated to the goal of a focal
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*activity, increasing the intensity of the knowledge-related activity will diminish the organizational learning rate associated with the focal activity*

**Aligned Goals and Learning-by-Teaching**

In contrast to the expected negative influence of diverse tasks with unrelated goals, when organizational goals are aligned (i.e., closely related), it facilitates the development of a strong culture and a more unified mindset, where individuals share the same general understanding of which types of actions are encouraged and which are discouraged during focal task implementation (O'Reilly, Chatman, and Caldwell 1991; Wiener 1988). Moreover, when employees have a central goal, their motivation to reflect and collectively learn from focal task experience may be heightened. Importantly, employees with shared goals are more likely to be consistent in their interpretation of what greater levels of performance actually mean for the focal task (e.g., efficiency, quality, etc.) as they seek improvement. Such shared meaning is likely to reduce communication errors and other inconsistent actions between employees in the implementation of the focal task (Carton, Murphy, and Clark 2014), improving the opportunity to learn from more accurate information and more effective collective reflection.

There is perhaps no activity that is more naturally related to the performance of a focal task than the teaching of that focal task. Nevertheless, to our knowledge, with one exception (DiStefano, Gino et al. 2014), the prior literature on learning-by-doing has given little attention to the potential role of teaching. Given this oversight in the literature, we believe that teaching is deserving of more direct conceptual consideration as it relates to the impact of goal-relatedness on learning-by-doing. Perhaps one reason why there has been a lack of attention to teaching in the learning literature is because teaching, while intuitively related to knowledge accumulation and learning in general (particularly in recipients), may be less intuitively related to learning-by-doing, especially when it comes to considering the learning of those teaching. Nevertheless, emerging paradigms in the field of professional education hold that one of the best ways to learn is to teach. This idea can be traced back to the first century philosopher Lucius Annaeus Seneca (Seneca the Younger), who said “docendo discimus” (Latin: "by teaching we are learning", Seneca 1920). In the field of education, Chase et al. (2009) report on a series of experiments in
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which students engaged in the act of teaching learned more than other students and that this occurred because those students put forth greater effort (i.e., engaged in more intensive search). Their study provides evidence that this effect was driven by a sense of responsibility for those they were assigned to teach, which in turn led them to increase their effort. In other words, taking responsibility for another’s learning can increase one’s own motivation to engage in search behavior.

In addition to the motivational boost gained from taking responsibility for another’s learning, prior research suggests that teaching also improves learning by increasing opportunities for reflection and feedback (Cortese 2005). As Cortese and colleagues (2005) observed in their study of the learning events experienced by managers, “teaching activities also provide the people involved with an important stimulus for reflection” (p. 98) in a way that breaks down resistance to change. This resistance to change is further broken down by an increased awareness of one’s own ignorance. Awareness is fueled both by one’s own preparations to teach (i.e., the act of organizing one’s knowledge reveals gaps), but perhaps more pointedly by the questioning and direct observations of the pupil. In this way, the social interaction between teacher and pupil serves as a feedback mechanism that provides the teacher with additional information about his or her own shortcomings. This argument is consistent with research in organizational knowledge creation that details how the process of converting tacit knowledge into explicit, codified knowledge typically involves cycles of interaction and exploration (Nonaka 1994). Thus, the act of teaching not only creates knowledge that is potentially complementary to the focal activity (through greater preparation, effort, and concentration), but goal alignment ensures its productive application through the interaction of the teacher and his or her pupils. From this perspective, teaching may be among the more powerful goal and knowledge-related activities when it comes to learning, not only for the pupil, but perhaps for the teacher as well. Thus, we expect that greater participation in teaching will enhance the learning of the teacher. At an organizational level, we believe this effect aggregates such that where a greater proportion of people are involved in teaching a focal activity, the greater will be their collective learning. Thus, we propose the following:

Hypothesis 3: Where the goal of a knowledge-related activity is related to the goal of a focal
activity, increasing the level of the knowledge-related activity will improve the organizational learning rate associated with the focal activity

Setting: Hospitals in the United States

We examine these issues in the hospital industry in the United States. More specifically, we explore these issues by examining the nature and extent of a hospital’s academic activities in the context of PTCA procedures performed by interventional cardiologists. We do so for two primary reasons. First, academic affiliations introduce diverse activities into the hospital’s clinical environment, including those with both related (teaching) and unrelated (research) performance targets. Not all hospitals are affiliated with medical schools, and some affiliate loosely, solely for the purpose of teaching resident physicians. We view the goals of teaching in this setting as well aligned with the goals of clinical care. Whereas the goal of clinical care is improved health outcomes for patients, the goal of teaching is to help resident physicians to develop the ability to provide those improved health outcomes. However, hospitals with the strongest medical school relationships (i.e., academic medical centers) also employ physicians with research-oriented faculty appointments as part of their internal organization. The research orientation of academic medical centers imposes additional performance targets on academic physicians, including pressures around grant funding and the “publish-or-perish” incentives associated with the pursuit of tenure. These pressures are similar to those faced by university faculty in other fields and do not explicitly align with those that would advance clinical care (e.g., good outcomes for patients).

Prior work has carefully described the general institutional logics associated with each of these activities (Dunn and Jones, 2010), noting that in medical schools the “science” logic has long played a prominent role (Zuckerman, 1977; Bloom 1988; Zerhouni, 2005). As Dunn and Jones (2010, pg 124) described, over time:

…Research in medical schools became more similar to basic sciences in other parts of the university than to the clinical research conducted by medical school faculty who study human subjects. Clinical research has provided fewer career incentives, leading some critics to claim that many medical schools have discarded the medical applications of their subjects to focus on the basic research necessary to attract funding from the NIH and advance researchers’ careers.

Despite this shift, even if we assumed that the research of interventional cardiologists does not
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pertain directly to performing PTCA (e.g., as in the case of research on the underlying disease processes associated with heart disease), the knowledge acquired should still be relevant to PTCA patients, since the “task” of effectively caring for PTCA patients in the hospital requires non-procedural knowledge pertaining to the patient’s underlying condition (e.g., how to monitor and evaluate heart function and blood flow; the key variables involved in selecting, evaluating and adjusting medications). Nevertheless, interviews with cardiologists, and a review of publications for a handful of leading interventional cardiologists², suggest that the work of these academic physicians tends to be more directly related to their clinical practice (i.e., directly related to PTCA). For example, one cardiologist we spoke with said, “my research examines the efficacy of different treatments [e.g., clinical trials] or the choices that cardiologists make. This is directly relevant to my own clinical work.” Another reported, “my research links to my practice as I’m studying the same thing that I’m doing.” Thus, in our setting, we examine an activity with strong potential for knowledge complementarities that also introduces unrelated goals to the organization.

Second, while there has been some trend toward specializing in research or patient care, industry studies have consistently suggested that in AMCs, the vast majority of physicians split their time between research pursuits and patient care (Thomas, et al. 2004; Pollart, et al. 2015). Even among physicians who say they prefer research work over patient care, patient care still represents a significant portion of their time allocation (Shannafort, et al. 2009). The splitting of physician time represents an important mechanism by which unrelated goals may influence both the opportunity and motivation to learn. For example, because academic physicians spend a significant portion of their time on research they naturally have less time available to perform procedures and engage in learning processes. Accordingly, for a given total volume of PTCA activity, academic medical centers must spread that volume across more physicians than non-academic facilities, leading to fewer opportunities for individual learning and less time devoted

² We reviewed publication titles for five interventional cardiologists included in our study and practicing in major academic medical centers. The results suggest that nearly two-thirds of their publications include words or phrases in the title that are directly related to PTCA. Details of this analysis are available from the authors upon request.
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to collective reflection. Moreover, the back-and-forth between the conflicting goals of research and patient care is likely to require significant cognitive resources (Monsell 2003; Staats and Gino 2012), leading to cognitive fatigue and a lack of motivation to engage in the cognitive processes required to enhance learning, even when the opportunity to do so is evident.

Finally, we note that prior studies in the fields of medicine and health services research have compared academic and non-academic hospitals (Rosenthal, et al. 1997; Polanczyk, et al. 2002). Reviews of this work suggest that, in general, academic hospitals provide better care than non-academic hospitals (Ayanian and Weissman 2002). Our study differs significantly from these studies in that these prior studies have defined academic status primarily based on the intensity of teaching and how non-teaching and teaching hospitals differ in terms of performance levels. In contrast, the key question we consider relates to the learning effect (i.e., the effect on the rate of performance improvement) of introducing the research-oriented goals of medical schools to the organization as distinct from the learning effect of teaching intensity, a question that has not been directly addressed by the empirical literature on academic hospitals. Many academic hospitals engage in both activities, and the question in our paper is whether these activities (which introduce multiple goals) exert separate and independent influences on learning-by-doing.

Data, and Empirical Strategy

Sample and Data

Our analysis examines cardiovascular patients who received Percutaneous Transluminal Coronary Angioplasty (PTCA). PTCA is a minimally invasive procedure in which a balloon catheter is fed from the femoral artery to the diseased portion of the coronary artery where the balloon is inflated to allow blood to flow freely around the blockage. PTCA is typically performed by an interventional cardiologist (IC). While some ICs have begun to add other therapeutic procedures to their repertoire, e.g., transcatheter aortic valve replacement (TAVR), angioplasty has long been the primary focus of ICs, and newer procedures did not gain wide acceptance until after our study period (e.g., TAVR was only approved by the FDA in 2011).
We chose to examine learning in this setting for several reasons. First, PTCA is a relatively new procedure; an innovation over preexisting approaches to treating heart disease. Though it was initially developed in the early 1980s, it did not gain wide acceptance and adoption until the mid-1990’s, when it experienced dramatic growth and overtook coronary artery bypass graft (open heart surgery) as the most utilized procedure for treating heart disease (Cutler and Huckman 2003). An additional innovation was introduced in 1994, when the US Food and Drug Administration approved the use of stents during PTCA procedures. By 1997, the use of stents had become commonplace and in 2003, drug-eluting stents were introduced, aimed at preventing the closure of the opened artery (restenosis). Second, comparisons across patients and hospitals are easier as PTCA is a well-documented and codified procedure, so as to be clearly distinguishable from other techniques by outside observers, regardless of the physician or hospital involved. PTCA patients are also relatively more homogenous than the broad population of cardiovascular patients. Cardiovascular patients not receiving PTCA tend to have more comorbidities and more advanced disease states than patients receiving PTCA. Third, PTCA is a procedure for which we can develop a well-defined, measurable outcome. We can determine whether the procedure failed (i.e., the patient died or necessitated a subsequent procedure) using hospital discharge data.

Our analysis examines PTCA patients using data on hospital discharges from the states of New Jersey and Maryland. These data were obtained from the State Inpatient Databases for New Jersey (NJSID) and Maryland (MDSID) from the Health Care Cost and Utilization Project (HCUP) of the Agency for Health Care Research and Quality. Data in the NJSID and MDSID are reported at the level of the patient and include information for every patient discharged from every acute care hospital in the state for a given year. These data include information about the hospital (e.g., location, teaching status), patient demographics, patient status upon discharge, the nature of the patient’s disease (e.g., primary and secondary diagnoses) and hospital stay (e.g., procedures performed). Using these data, we estimate learning curve models at the hospital level.

We develop our sample and variables based on the NJSID and MDSID between 2000 and 2008. We matched these data with information on individual hospitals from the American Hospital Association.
(AHA) annual survey of hospitals over the same time period. Over this time period 352,073 patients received PTCA procedures in 96 New Jersey and Maryland Hospitals. We excluded patients (31,306) whose primary diagnosis was something other than cardiovascular disease. Information on our key independent variables of interest (as described below) was only available for a subsample of hospitals and hospital-years from the AHA annual survey, meaning that an additional 26,397 patients were excluded from the analysis. Of these, 1,486 were missing medical school affiliation information and 24,911 were missing both medical school affiliation and teaching intensity information from the American Hospital Association annual surveys. Finally, 2,585 observations were excluded due to the lagging of our key independent variables and 285 observations were excluded due to missing demographic or admission type information. After accounting for these exclusions, our dataset included 291,500 patients receiving PTCA in 72 New Jersey and Maryland hospitals. As described below, we aggregated data on these patients in order to examine our hypotheses at the hospital-quarter level and further limited our base sample to hospitals meeting a minimum volume threshold. Our final base sample included 52 hospitals, representing 984 hospital-quarters between 2000 and 2008.

**Dependent Variable**

A natural outcome to focus on for heart disease is patient mortality. However, in the case of patients receiving PTCA, death is a rare outcome (<1% of patients). Accordingly, we focus our attention instead on a more prevalent outcome that also reflects procedure failure: the rate at which patients in a particular hospital require another procedure, or re-work. Procedures were classified as “rework” if one of two events occurred: (1) the patient required Coronary Artery Bypass Graft following PTCA, or (2) the patient received a “repeat” PTCA procedure following the first. To ensure that a second PTCA procedure was in fact re-work, we restricted our identification to procedures that occurred on a subsequent day following the primary procedure. Our outcome variable of interest, *Rework*, is a measure of the rate at

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3 This threshold, described in our discussion of the dependent variable, is intended to address possible small sample bias in the calculation of risk-adjusted outcomes. We test the robustness of our findings to this threshold, including running our models on the full sample of 72 hospitals to see if the same pattern of results holds.
which initial procedures result in a corrective procedure during a patient’s hospitalization for PTCA.

Because of heterogeneity in patient characteristics, raw rework rates may be a biased measure of performance. Accordingly, we estimate risk-adjusted rework (\(RARW_{jt}\)) for each hospital \(j\) in quarter \(q\) of year \(t\) using a logistic regression. The outcome variable in this regression is \(REWORK_{ijqt}\), an indicator that equals one if patient \(i\) in hospital \(j\) in quarter \(q\) of year \(t\) required a rework procedure while in the hospital, and zero otherwise. The specific form of this regression follows:

\[
\ln \left( \frac{pr(REWORK_{ijqt}=1|x_i)}{1-pr(REWORK_{ijqt}=1|x_i)} \right) = \alpha + \beta_1 X_i + \epsilon_{ijqt} \quad (1)
\]

\(X_i\) represents a vector of patient-level risk factors, including patient demographics (patient age, patient gender, and their interaction), proxies for patient severity (emergency versus routine admission, number of procedures and diagnoses) and co-existing conditions. With respect to the latter, we use a common method—the Elixhauser (1998) method—for risk adjusting patient severity that entails including indicators of the presence or absence of secondary diagnoses in 30 disease categories.\(^4\)

To aggregate the results of this regression into hospital \(j\)’s risk-adjusted rework rate, we averaged the predicted values from (1) for hospital \(j\) in quarter \(q\) of year \(t\) to create a predicted rework rate \(PRW_{jt}\). We calculated each hospital’s observed rework rate \(ORW_{jt}\)—the total number of rework cases at each hospital for the relevant time period divided by the total number of PTCA patients in the hospital over the same time period. These two values were used to calculate \(RARW_{jt}\) as follows:

\[
RARW_{jt} = \frac{ORW_{jt}}{PRW_{jt}} \times ARW \quad (2)
\]

ARW represents the average rework rate across all hospitals during the study period and is used to normalize and center the risk-adjusted rate. Consistent with industry standards (Pennsylvania Health Care Cost Containment Council 2007) and prior work that has taken a similar approach to risk-adjustment.

\(^4\) These include indicators for congestive heart failure, cardiac arrhythmias, valvular disease, pulmonary circulation disorders, peripheral vascular disease, hypertension, paralysis, other neurological disorders, chronic pulmonary disease, diabetes (uncomplicated), diabetes (complicated), hypothyroidism, renal failure, liver disease, peptic ulcers, AIDS, lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis, coagulopathy, obesity, weight loss, fluid and electrolyte disorders, blood loss anemia, deficiency anemias, alcohol abuse, drug abuse, psychoses, depression.
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(Clark and Huckman 2012), we exclude low volume hospitals and only include those that performed at least 20 procedures in a given quarter. By doing so, the final sample for our analysis includes 52 hospitals. While our choice of 20 procedures is somewhat arbitrary, we examine the robustness of our findings to this choice in the results section of the paper.

**Independent Variables**

In order to assess learning, we measure each hospital’s cumulative prior experience performing PTCA. More specifically, we calculate *Experience* on a quarterly basis dating back to 1999\(^5\) and lag the measure one quarter relative to the quarter in which the current patient’s PTCA procedure was performed. By lagging the variable we capture the hospital’s experience prior to the quarter in which the procedure occurred. Thus, for a patient receiving PTCA in a New Jersey hospital in March of 2004, *Experience* equals the total number of PTCA procedures performed by the hospital from January 1999 through December 2003.

We test our key hypotheses by considering the learning effect of academic affiliation in the hospital industry. We capture the intensity of academic affiliation using indicators for the strength of a hospital’s connection with a medical school. While most hospitals are not affiliated with medical schools, some have relatively loose affiliations (e.g., to allow for teaching, but not necessarily research), and others have very strong ties that allow for significant research and teaching. We capture these ties based on information reported on the American Hospital Association (AHA) Annual Survey from 2000 through 2008. We identify the strongest of these ties using a variable that indicates whether or not a hospital was a member of the council of teaching hospitals and health systems (COTH). COTH members represent the most exclusive group of hospitals, a group that is commonly (and appropriately) referred to as Academic Medical Centers (AMC). As the name implies, AMCs introduce a heavy academic presence within the hospital. In contrast to these organizations, some other hospitals are affiliated with medical schools, but the strength of the relationship and the academic presence are much less intense. These hospitals are captured using a variable that indicates whether or not the hospital had any medical school affiliation,

\(^5\) We had NJSID and MDSID for 1999, but did not have 1999 AHA survey data. Accordingly, we are able to chart a hospital’s experience performing PTCA since January 1999, but are unable to include these patients in the analysis.
after excluding those that are COTH members. Incorporating hospitals with no affiliation, we combine these classifications to create a categorical variable, *Academic*, with three levels: no academic affiliation (*Academic0*), non-COTH medical school affiliated (*Academic1*), and AMC COTH members (*Academic2*). In our models, these variables are lagged by one year to improve causal identification.

In order to distinguish the aspects of academic affiliation that we have conceptualized as goal-unrelated (e.g., academic research) from goal-related ones (e.g., teaching), we employ a direct measure of teaching intensity. By controlling for the intensity of teaching separately, the estimated effect of *Academic* should relate primarily to activities that we have argued are more unrelated to clinical care in terms of goals and performance targets. We measure the extent of teaching activity in hospitals based on the number of interns (observational training during medical school) and residents (supervised, hands-on, post-medical school training) per hospital bed. This measure (labeled *Teaching*), also derived from the AHA Survey, is commonly used in the medical and health services research fields to capture teaching intensity in hospitals (Shortell and LoGerfo 1981; Volpp et al. 2007). This variable captures the extent to which each organization is engaged in coaching and mentoring individuals receiving observational and hands-on training in regular work settings (as opposed to training conducted outside of regular work sessions, such as a retreat). This variable is lagged by one year to improve the causal identification of our models. Table 1 presents summary statistics and correlations of our key variables of interest.

[Insert Table 1 about here]

Finally, we control for two hospital characteristics that may be related to the level of experience and the teaching and research activities of the hospitals in our study. First, we control for relative market share. We measure relative market share as the ratio of a hospital’s own market share to the market-leading hospital’s market share (for non-market leaders) or the ratio of the market leading hospital’s market share to the second leading hospital’s market share. This variable allows us to capture multiple,
related characteristics, including competitive position, availability of resources, and size. \(^6\) Second, we proxy for prior technical quality. We do so based on a given hospital’s mortality rate for PTCA procedures in the preceding quarter preceding. We use mortality and not rework because in a fixed effects model, lagged dependent variables can introduce “Nickell Bias” (Nickell 1981). The issue comes down to the correlation between the lagged dependent variable and the error term, which arises because of the strong correlation between the lagged measure and the dependent variable itself. Our lagged (i.e., prior period) measure of mortality should not suffer from this problem because it demonstrates a relatively weak correlation with our dependent variable measured in the current period (\(r < 0.30\)). In our models, each of these control variables are also interacted with Experience.

**Empirical Models**

We estimate organizational learning curves using a log-binomial model to estimate \(RARW_{jqt}\). The log-binomial is a generalized linear model in which the link function is the natural log of the rate being studied, in this case \(RARW_{jqt}\), and the distribution of the errors is binomial. We test our hypotheses using this model for two reasons. First, the log-binomial provides a functional form that is identical to the functional form theoretically derived by Lapre and Tsikritis (2006) for use in organizational learning curve models. While the power form has long been used in learning curve studies, Lapre, et al (2000) and Lapre and Tsikritis (2006) provide theoretical justification for the superiority of the exponential form, first presented by Levy (1965). The theoretical derivation of this model in the context of organizational learning curves results in the following functional form (Lapre and Tsikritis 2006, pg. 356):

\[
\ln(\pi) = \alpha + \mu E \quad (3)
\]

Where \(\pi\) is the rate under study, \(\mu\) is the learning rate and \(E\) is the experience variable. By estimating a basic log-binomial model, the functional form of this model in the context of the variables used in our study is identical to the one derived by Lapre and Tsikritis (2006):

\(^6\) We note that relative market share is highly related to size in our data (\(p > 0.80\)). Accordingly, we do not control for size, preferring relative market share for its direct conceptual link to competitive positioning (and by extension aspirations).
The second reason we rely on this form of the learning curve has been summarized by Lapre and Tsikritsis (2006, pg. 356): “If organizations operated before the availability of data on the outcome measure, omission of prior experience will bias learning-rate estimates...for the exponential form, accounting for prior experience is a nonissue—omission of prior experience will not bias learning-rate estimates.”

Building on this model, we begin examining our hypotheses with a base specification, as follows:

\[
\ln(RARW_{jtq}) = \alpha + \sigma_j + \gamma_t + \beta_1 Experience_{jtq-1} + \epsilon_{jtq} \tag{5}
\]

Where \(\sigma_j\) and \(\gamma_t\) represent hospital and year fixed effects, respectively. The latter is included to control for unobserved factors that may drive the average likelihood of mortality over time, and the former to control for time invariant hospital attributes that relate to our key variables of interest and the likelihood of mortality. \(Experience_{jtq-1}\) represents cumulative experience for hospital \(j\), in year \(t\) and quarter \(q-1\).

We note that this base model does not include the other key independent variables (i.e., Academic and Teaching) or control variables.

To test hypotheses 2 and 3, we build on (5), adding the Teaching, Academic and control variables, building a fully specified model that includes all of the interaction terms, as in (6):

\[
\ln(RARW_{jtq}) = \alpha + \sigma_j + \gamma_t + \beta_1 Experience_{jtq-1} + \beta_2 Teaching_{jt-1} + \beta_3 [Teaching_{jt-1} * Experience_{jtq-1}] + \beta_4 Academic1_{jt-1} + \beta_5 [Academic1_{jt-1} * Experience_{jtq-1}] + \beta_6 Academic2_{jt-1} + \beta_7 [Academic2_{jt-1} * Experience_{jtq-1}] + \beta_8 X_{jtq-1} + \epsilon_{jtq} \tag{6}
\]

Where \(\sigma_j, \gamma_t, Experience_{jtq-1}\), and each of the contextual variables are as described previously and \(X_{jtq-1}\) is a vector of the control variables described previously and their interactions with \(Experience\). We note that in the context of the outcome variable under study, a lower value (i.e., fewer cases of rework) is better. We also note, that the results of our log-binomial estimation strategy are presented in terms of relative risk ratios, where values greater than one signify positive effects and values less than one signify negative effects. By reporting relative risk ratios, we are able to directly interpret the magnitude and
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significance of interaction terms as multiplicative effects in our non-linear models (Ai and Norton, 2003; Buis 2010). Thus, our hypotheses can be restated as follows:

\[
Hypothesis 1: \beta_1 < 1; \quad Hypothesis 2: \beta_7 > 1; \quad Hypothesis 3: \beta_3 < 1
\]

**Results**

Table 2 presents the results of our base specifications. Column 1 presents results without the moderating and control variables, column 2 includes the moderators without interactions, and column 3 adds the interactions to the model. Columns 4 and 5 add the controls and control interactions, respectively. The results in column 1 suggest that experience has a negative relationship with RARW (i.e., risk ratio < 1). In our case because less rework is a good thing, the relative risk ratio reported represents improved performance. Thus, the results in column 1 are consistent with hypothesis 1, though the estimate is not statistically significant according to conventional thresholds.

![Table 2 About Here](image)

The results in column 5 represent the primary test of hypotheses 2 and 3. With respect to hypothesis 2, the estimates on the interaction terms between the levels of Academic and Experience are positive (i.e., risk ratios > 1). Again, given that higher levels of rework are bad, this suggests that academic, research-oriented affiliations have a diminishing influence on the rate at which hospitals learn from their experience with PTCA. Moreover, the estimate for the interaction with Academic2 is significantly greater than the estimate for the interaction with Academic1, suggesting that the learning rate is in fact diminishing in the level of research orientation, with the highest level of research orientation associated with the slowest pace of learning. These findings are statistically significant (p < 0.01) at conventional levels. A graph of these results in the form of estimated learning curves by level of academic affiliation is presented in Figure 2. The graph suggests that while academic medical centers (AMCs) (Academic2) appear to do better (than unaffiliated hospitals) in the absence of experience, the rate at which they learn from experience, on average, leads to a very small amount of improvement as experience accumulates. In contrast, unaffiliated hospitals (Academic0) demonstrate significant improvement. Similarly, medical school affiliated hospitals (Academic1) do better both in the absence of
experience and as it accumulates. Thus, our results support hypothesis 2, suggesting that activities that introduce unrelated goals slow the rate at which organizations learn from experience.

With respect to hypothesis 3, the estimated relative risk on the interaction term between Teaching and Experience is less than one. This suggests that teaching intensity has an amplifying influence on the rate at which hospitals learn from their experience with PTCA. In other words, the more hospitals engage in teaching the faster they learn from their experience. These results are statistically significant (p<0.001) at conventional levels. A graph of these results in the form of estimated learning curves by level of teaching intensity (i.e., interns and residents per bed, or IRB) is presented in Figure 3. The graph suggests that while hospitals with a heavy teaching emphasis (40% IRB) appear to do worse in the absence of experience, the rate at which they learn from experience, on average, leads to substantial improvement as experience accumulates. In contrast, hospitals with no teaching demonstrate improvement, but at a substantially reduced rate. These results support the general idea associated with hypothesis 3, that goal-related activities have a complementary relationship and enhance learning. They also support the idea that teaching activities are a potentially powerful way to enhance the rate at which organizations learn from their experience.

Robustness

Our paper is concerned with empirically addressing organization-level questions. Accordingly, we aggregated our raw, patient-level data to examine it at that level. In doing so, we recognize that we may lose some information and variability that has a material impact on our results. To test this possibility, we ran patient-level analyses, with a binary version of rework as the dependent variable. Normally, we would rely on a logit or probit alone to estimate these models. However, in our case a traditional logit is problematic for two reasons. The first is a practical problem: due to the incidental parameters problem, a traditional indicator variable approach to fixed effects may bias the results and, thus, the ideal is instead to estimate a conditional logit. With hundreds of thousands of observations, we
were unable to get a conditional logit model to converge. Thus, we were left with the traditional approach to fixed effects (and the incidental parameters problem). The second issue relates to the difficulty of interpreting interaction effects in logit models. Because of the multiplicative nature of logit models, interaction terms cannot necessarily be interpreted directly both in terms of the direction and significance levels (Ai and Norton 2003). Given these issues, we also run a linear probability model to see if the estimated marginal effects on the interaction terms appear to be impacted in the logit by the incidental parameters problem and the multiplicative nature of logit models. The results of both models are reported in columns 1 and 2 of Table 3. The estimates suggest that our baseline findings are not biased by the choice to aggregate the data to the organization level.

[Insert Table 3 About Here]

Our primary measures of academic affiliation and research orientation are categorical in nature. While we believe our use of hospital fixed effects largely addresses omitted variable bias in our analyses, our data does allow us to test some alternative explanations for our findings. Specifically, it is possible that our findings with respect to academic affiliation may be explained by differences in resource allocation practices (e.g., workload assignments), or general management practices, or perhaps the breadth of service offerings. Accordingly, we developed proxies for each of these possibilities. We measure resource allocation practices based on the average workload of nurses in each hospital (i.e., ratio of FTE nurses to the average daily census). We capture management practices based on whether or not a hospital has achieved “Magnet” status with the American Nurses Association, a designation that is largely based on practices (e.g., nurse autonomy and clinical authority) that are deemed highly attractive to the nursing profession (Aiken, Havens, and Sloane 2000). Finally, we capture services based on the presence or absence of 69 services as tracked by the AHA annual survey between 2000 and 2008. Our measure of service breadth is the simple sum of the total number of these services offered by each hospital. Table 3 presents the results of models in which each of these potential confounders, along with its interaction with experience, is entered into the model individually (columns 3-5) and then collectively (column 6). We note that differences in the number of observations across the models are due to missing data for the
service breadth measure. The results suggest that our findings with respect to teaching and academic affiliation are consistent across all models and unaffected by the inclusion of these additional variables. These results give us additional confidence that our measure of academic affiliation is, in fact, isolating goal-conflict and not some other related characteristic of academic medical centers.

We acknowledge that any endogeneity with respect to our key explanatory variable, Experience, may lead to biased estimates. Specifically, we recognize that hospitals with higher-quality PTCA programs may attract larger volumes of PTCA patients, thereby increasing their cumulative experience with PTCA. The combination of lagging Experience and including hospital fixed effects is a typical approach in the literature (e.g., Huckman and Pisano 2006) to dealing with this endogeneity concern. However, the nature of our data allows us to take several additional steps to address this issue. First, we can directly test for reverse causality by running a reverse regression model. Specifically, we ran a model in which a hospital’s PTCA experience was used as the dependent variable and RARW, lagged one time period, was included as the key independent variable. The model includes hospital fixed effects and year fixed effects. If Experience was endogenously related to performance, we would expect to find a negative and significant relationship between the risk-adjusted Rework rate and future cumulative volume. The results suggest that if, anything, the relationship runs in the opposite direction from what would be expected if endogeneity were a concern in our main analyses. Specifically, the coefficient on RARW is positive but only weakly significant (p=0.068). To the extent that there is a relationship there, it appears to be working against our observed findings. Thus, these results help to mitigate the concern that a hospital’s level of experience is endogenously determined by prior performance.

The second way we address this endogeneity concern related to patient self-selection, is to limit our analysis to those patients who have limited or no choice in the hospital they visit to receive care. This

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7 The Experience model is specified as follows, where, as before, $\alpha_j$ and $\lambda_t$ are hospital and year fixed effects, respectively: $Experience_{j,t} = \alpha_j + \gamma_t + \beta_1 RARW_{j,t-1} + \beta_7 X_i + \epsilon_{jqt}$
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is the case with patients whose conditions are more urgent. Because the law (and common sense) requires that ambulances take patients to the nearest hospital (and not their hospital of choice), by limiting our analysis to patients in urgent and emergent situations, we are able to address the potential for selection bias in our results. Accordingly, we examine two additional models in which our sample is limited to (1) urgent and emergency patients, and (2) emergency patients only. In addition, our models measure experience based solely on the hospital’s experience with emergent or emergent/urgent patients. Finally, we run models in which we also control for (1) PTCA experience with patients who are not urgent or emergent, and (2) PTCA experience with patients who are not emergent. These latter models give us some sense whether our results with respect to the more exogenous emergency experience are biased by the exclusion of the more endogenous, but potentially related non-emergency experience. These models are presented in Table 4, columns 1-4. The results are highly consistent with the findings of our base models. We note that while the level of significance on the emergent volume estimate in column 3 has gone down slightly with the inclusion of non-emergent volume (p = 0.055), the magnitude of the estimate has gone up, demonstrating that the change in statistical significance is likely due to variance inflation caused by the non-emergent volume variable. Thus, while not completely mitigating the potential for endogenous selection, these results give us significantly greater confidence that our findings are not biased by this issue.

[Insert Table 4 About Here]

We acknowledge that by focusing our outcome variable on rework, we have largely ignored another important, but relatively less prevalent, outcome in our setting: death. In order to evaluate this outcome, we examined two alternative dependent variables: death and failure. In the case of death, risk-adjusted mortality (RAMR) is defined similar to RARW, with rework replaced in the logistic regression by a binary indicator for whether the individual died while hospitalized. With respect to failure, risk-adjusted failure (RAFR) is also defined similar to RARW, with rework replaced in the logistic regression by a binary indicator for whether the individual experienced either death or rework while hospitalized. In this sense, RA FR captures the presence (or absence) of three outcomes: repeat PTCA, CABG following
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PTCA, and death. Though we do not report the results of these robustness checks here, the results in all cases are largely consistent with the base findings reported in Table 2. Notably, the estimated effects with respect to \( \text{RAMR} \) are diminished, though we expected this given the relative rarity of the outcome in this setting. Moreover, when death is accounted for along with rework, the results are highly consistent with our base results. These findings suggest that our results are largely robust to the choice of outcome measure.

Finally, our base results were estimated on a sample of hospitals that excluded low volume hospitals. More specifically, we limited our sample to the 52 hospitals that performed at least 20 procedures in a given quarter during our study period. We tested the sensitivity of our findings to this choice by examining minimum volume thresholds of zero, 15 and 30 cases. For each minimum volume threshold, we include results with and without the additional variables described in the previous paragraph. Again, we do not show the results of these tests here, but we note that the estimates are consistent with the results presented in Table 2 and are consistent across models. These findings provide us with confidence that our results are not a product of the minimum volume threshold.

Discussion

Our results suggest that goal relatedness across the diverse activities of an organization can have an important influence on the rate at which it learns from experience. More specifically, we find that diversifying into activities that are knowledge-related, but goal-unrelated, diminishes the rate of learning with respect to a focal activity. In contrast, diverse activities that are both knowledge- and goal-related enhance the rate at which organizations learn from focal task experience. In the context of our study, this latter finding provides evidence supporting a learning-by-teaching effect.

Our findings along these lines are of practical significance. With respect to activities that are goal-unrelated (i.e., research), our findings suggest that academic medical centers learn at a significantly slower rate than unaffiliated, non-research hospitals, with estimates suggesting that a typical unaffiliated (non-academic) hospital improves its rate of rework from more than 6 percent to just under 3 percent over the course of the first 10,000 cumulative procedures performed. With respect to activities that are goal-
related (i.e., teaching), our findings suggest that for hospitals starting with similar levels of performance (e.g., a rework rate of about 4%) and cumulative experience (e.g., 5,000 cases), the next 10,000 cases result in a nearly 3 percentage-point reduction in the rework rate for heavy teaching hospitals but only a half percentage-point reduction for non-teaching hospitals. These estimated learning rates suggest that hospitals with activities that are more goal-related learn at a rate sufficient to push their rate of rework near zero over the relevant range of experience in our study. If all hospitals performing PTCA were designed accordingly, such that the average rate of rework fell from the 3.2% average in our data to near zero (e.g., 0.25%), we estimate that the US health care system would save $424 million annually—$2.1 billion every five years—due to the incremental cases of rework avoided.8

Given the statistical and practical significance of our findings, our study makes several important contributions to the learning literature. First, we find that even if areas of activity are knowledge-related (e.g., medical research and clinical practice), learning suffers if the goals and corresponding performance targets are not aligned (publish-or-perish vs. patient outcomes). These findings are consistent with the operations strategy literature, which has cautioned firms against pursuing too many goals or attempting to compete on every yardstick (Huckman and Zinner 2008). Moreover, our findings contribute to a relatively nascent but growing literature in organizational theory that explores the repercussions of pursuing multiple, weakly correlated or uncorrelated, goals within an organization (Kerr 1975; Ethiraj and Levinthal 2009). Specifically, recent work in this domain has shown that the imposition of multiple goals can lead to a “freezing in behavior towards the status quo” (Ethiraj and Levinthal 2009). Our study contributes additional insight into why this “status quo bias” with respect to performance might arise—the introduction of additional unrelated goals limits the ability of organizations to learn from experience.

8 In calculating this estimate, we assume that there are approximately 600,000 PTCA procedures performed in the United States each year. We also assume that among patients requiring rework, the share receiving repeat PTCA and the share receiving CABG is the same as it is in our data set, 71% and 29%, respectively. We also assume a baseline cost figure for repeat PTCA and CABG based on Medicare reimbursements for these procedures ($18,985 and $43,107, respectively). Finally, we assume that Medicare reimbursements are approximately 70% of private insurance reimbursements and that approximately 50% of the patients needing rework are on Medicare (as in our dataset). More details are available from the authors upon request.
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Conversely, we also show that when organizations introduce tasks that are well aligned with the existing goals of the organization, they can increase the rate at which they learn from experience. As a result, we provide a strong rationale for managers to look beyond knowledge-relatedness, and consider goal-relatedness, when they seek to diversify their organization’s activities.

Our theoretical framework suggests that these learning effects work by the influence of goal-relatedness on both the opportunity and the motivation to learn from experience. One potential alternative to this explanation is that it’s not goals, but rather degrees of knowledge-relatedness, that matter. In other words, the research of faculty physicians is less knowledge-related than teaching, leading to a diminished impact of research on learning. We note that even if medical research was less related to clinical care than teaching, prior work on knowledge-relatedness suggests that it should still have a positive, though lesser, impact on learning (Clark and Huckman 2012; Schilling, et al. 2003). Our results are not consistent with this prediction, suggesting instead that research has a significant negative impact on learning. In exploring this alternative explanation further, our analysis of the publication records of five academic interventional cardiologists in our sample suggests that a significant majority of the publications are directly concerned with PTCA (e.g., a paper about the impact of comorbidity on PTCA outcomes). In addition, while we cannot test our proposed goal-relatedness mechanisms directly, we are able to explore whether the pressure to meet academic goals (as in academic medical centers) leads academic physicians to devote less time to (and accumulate less experience from) patient care. Using a few select years from our data set (Maryland only, where reliable physician IDs were available for select years), we calculated the average annual PTCA volume per physician by hospital type (see Figure 4). In line with our framework, the results suggest that, on average, non-academic interventional cardiologists do more than twice as many procedures annually as academic physicians. This lower average volume suggests that academic physicians split their time between teaching and research and that, for a given accumulation of PTCA experience, the adoption of unrelated goals necessitates that the organization spread its volume across more individuals. The result is both fewer opportunities for individual learning (in the form of both fewer experiences and less time for reflection) and greater fragmentation of any learning that does accrue.
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Moreover, the constant switching between the academically-oriented goals of research and the patient-oriented goals of clinical care, is likely to increase cognitive fatigue (Monsell 2003; Staats and Gino 2012), reducing the motivation to learn from experience.

[Insert Figure 4 About Here]

In contrast to our findings with respect to academic affiliations, our findings with respect to the teaching intensity in hospitals correspond to a learning-by-teaching effect. While this effect has received some limited attention in the literature at the individual level, we are not aware of any theoretical or empirical treatments at the level of the organization. This oversight is surprising, given how much has been written about learning in organizations and the natural connection between learning and teaching. Some scholars have recognized a role for the concept of teaching in organizations. Most notably, Peter Senge’s (1990) work on the learning organization argues for a reformulation of the leader’s role to include the idea of leader-as-teacher. Our findings not only support this idea, but also take it a step further, suggesting that the role of teacher need not (perhaps should not) be limited to formal leadership roles. Indeed, our findings suggest that the benefit of teaching depends on how deeply teaching activities pervade the organization. From this perspective, there may be important benefits that can be derived from infusing teaching (and the role of teacher) at all levels of the organization. Such an approach may necessitate a recognition that everyone has something to teach. This way of thinking is consistent with the principle of Jidoka from the Toyota Production System, which empowers line workers to both identify problems and aid in solving them (Ohno 1988). Such a system effectively pushes teaching and learning in organizations as far down the “chain of command” as possible. To further understand the learning-by-teaching effect, future work should seek to disentangle the reciprocal value that accrues to both teacher and student in the process.

Finally, our findings broadly contribute to our understanding of the role of context in learning-by-doing. Argote and Miron-Spektor (2011) have noted that our understanding of the context within which learning takes place is limited, positing that, “Experience interacts with the context to create knowledge (p. 1124).” Our paper confirms this general assertion by focusing on one specific attribute of the context.
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i.e., the goals of the organization. In the process, we draw a link between an organization’s “active context” (i.e., its chosen activities) and its “latent context” (i.e., the goals and performance targets those activities impose on the organization). Thus, our empirical test of these ideas is the first to provide evidence that learning depends not simply on the immediate task environment—the “active context” in which experience is gained—but also on the organization’s “latent context” (Argote and Miron-Spektor, 2011).

Conclusion

Organizations continue to exhibit wide variation in rates of learning. By considering relatedness from a goal perspective, rather than a knowledge perspective alone, our paper makes important contributions to both theory and practice. Our results highlight that a key reason why not all experience is created equal, is that not all experience occurs within the same context. Specifically, by understanding how goal-relatedness aids learning we provide insight into how organizations can continuously improve and therefore build and maintain competitive advantage.

References


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Table 1: Summary Statistics and Correlations

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Table 2: Base Regression Results

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Model Additions

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<th>Key Independent Variables (IV)</th>
<th>Add Interactions w/Key IVs</th>
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Coefficients exponentiated and reported as relative risk ratios. Robust standard errors are clustered by hospital and shown in parentheses. All models include hospital and year fixed effects.

* p < 0.10, ** p < 0.05, *** p < 0.01
Table 3: Robustness—Addressing Alternative Explanations

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<td>0.917**</td>
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<td>(0.781)</td>
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<td>1.181</td>
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<td>(0.212)</td>
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Coefficients exponentiated and reported as relative risk ratios. Robust standard errors are clustered by hospital and shown in parentheses. All models include hospital and year fixed effects. Differences in observations are due to missing values for the service breadth and quality variables.
* p < 0.10, ** p < 0.05, *** p < 0.01
## Table 4: Robustness—Sample Limited by Degree of Urgency

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<td>0.760$^{***}$</td>
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<td>(0.035)</td>
<td>(0.081)</td>
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<td>(0.245)</td>
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<td>(0.159)</td>
<td>(0.074)</td>
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<td>0.768$^{**}$</td>
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<td>(0.263)</td>
<td>(0.081)</td>
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</table>

Coefficients exponentiated and reported as relative risk ratios
Robust standard errors are clustered by hospital and shown in parentheses
All models include hospital and year fixed effects

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