Incremental Organizational Learning from Multilevel Information Sources: Evidence for Cross-Level Interactions

Andreas Schwab, Louisiana State University
Incremental Organizational Learning from Multilevel Information Sources: Evidence for Cross-Level Interactions

Andreas Schwab
E. J. Ourso College of Business
Rucks Department of Management
Louisiana State University
3152 CEBA
Baton Rouge, LA 70803-6312
Tel: (225) 578-6249
Fax: (225) 578-6140
Email: aschwa3@lsu.edu

Published in
Organization Science

Reference:

I am grateful to Anne Miner, Henrich Greve, Craig Olson, James Moore, Yves Damoiseau, Jim Cater, Steve Michael, and three anonymous reviewers for helpful comments on earlier drafts of this paper; Jerry Jackson for data provided; and Randi Huntsman, Rebecca Nochta, Eric Hillebrand, and Katherine Bedeian Kingsmill for editorial assistance.
Incremental Organizational Learning from Multilevel Information Sources: Evidence for Cross-Level Interactions

Abstract

The availability of both direct performance feedback at the organization level and vicarious information at the industry level raises the question of their relative impact, as well as potential multilevel interactions. Prior research suggests that an organization’s own experience after adopting an innovative managerial practice tends to replace information collected by observing other organizations that implement the practice. The findings in this study show, however, that both organization-level performance feedback and population-level comparisons to other organizations affected incremental change of an innovative practice during its execution. The effects of these two information sources are not independent. Instead, results support a substitutional cross-level interaction. In addition, the study discovered that, when learning from their own experience, organizations engage in superstitious learning and do not let sufficient time pass before assessing effects of prior changes. This study identifies principles that will promote a more integrated understanding of learning during the execution of innovative practices and contributes to the development of more fine-grained multilevel models of organizational learning.

Keywords: Incremental Learning, Cross-Level Interaction, Performance Feedback Learning, Vicarious Learning, Superstitious Learning
After adopting an innovative practice, organizations typically face learning challenges associated with modifying it to optimize potential positive performance effects (Leonard-Barton 1988, Repenning and Sterman 2002). Firms may adjust the adopted practice incrementally based on direct performance feedback (Greve 2003b, March 1991) and indirect information gleaned from vicarious observations of how similar organizations have implemented the same practice (Baum et al. 2000, Miner and Haunschild 1995). This paper investigates incremental organizational learning in the context of the farm team system—a human resource innovation that emerged in the U.S. baseball industry during the 1920s. Farm teams enabled major league clubs to use a network of affiliated minor league clubs to discover and develop player talent.

Prior research has established the positive impact of this HR innovation on overall organizational performance and the important role of organization and industry-level experience in this context (Olson and Schwab 2000, Schwab et al. 2002). The current study, however, does not focus on organizational performance effects related to the adoption of this innovative practice. Instead, this study adopts a more fine-grained perspective and investigates incremental changes made after an innovation has been adopted. It focuses on the adjustment of a single key innovation trait—the decision to maintain or change farm team network size (the number of minor league teams in a major league club’s farm team network). The availability of relevant information at the organization level (performance feedback) and industry level (vicarious observations) presents a unique opportunity to not only investigate their respective importance, but also if and how they potentially interact—a topic of current debate in the learning literature (Crossan et al. 1999, Halebian et al. 2006, Haunschild and Beckman 1998).

This study addresses two limitations in the organizational learning literature as identified by March (1999): (1) a bias towards the investigation of performance as a learning outcome and (2) the lack of research on cross-level effects. This paper first outline the rationale underlying any direct effects of available information from the two different sources as input for incremental learning activities before investigating their potential cross-level interaction effects.
THEORETICAL FRAMEWORK

Organizational Learning

Organizational learning occurs when experience systematically alters behavior or knowledge (Argote 1999). Contemporary empirical research shows that learning affects not only if and when organizations adopt an innovative practice, but also influences incremental adjustments made during the execution of the practice (Edmondson et al. 2001, Leonard-Barton 1988, Repenning and Sterman 2002, Tyre and Orlikowski 1994). Interdependent and complex innovations that require integration with pre-existing organizational structures and processes present substantial continuing learning challenges that the management literature and organizations tend to underestimate (Robertson et al. 1996, Szulanski 1996).

Research on experiential learning has focused primarily on performance outcomes (March and Sutton 1997) or outcomes closely linked to performance, such as quality improvements (Levin 2000) or product development time (Eisenhardt and Tabrizi 1995). Mounting evidence, however, indicates that the link between specific implementation choices and performance improvements can be quite tenuous (March 2006). Related learning attempts can fail due to the paucity, ambiguity, or richness of experience (March et al. 1991), or because the knowledge gained is incorrect or irrelevant (Denrell 2003, Levinthal and March 1993). Even if an organization gains valid knowledge, other factors, like competitors’ actions or failure to apply the knowledge correctly, may prevent the firm from benefiting from the acquired knowledge (Greve 1996, Kim and Miner 2000). Consequently, important learning activities may not be captured or understood if organizational performance is the sole measure of learning outcome (March and Sutton 1997). The study of intermediate learning outcomes, such as adjustment of an adopted innovation’s key features, may help to reduce some of the research design challenges associated with distal causal links and promises a more comprehensive understanding of underlying multi-step learning activities.

Multilevel Perspective

The organizational learning literature has long argued that information from different levels of analysis is likely to interact (Crossan et al. 1999, Cyert and March 1963, March 1991). These conceptual
arguments are supported by simulation models (Carley 1999, Lounamaa and March 1987), but solid empirical evidence for these theoretical claims remains scarce. Most of the multilevel research in the management literature has focused on direct effects across individual, group, and organization levels (Bass 2000, Klein et al. 1999). In contrast, this study focuses on moderator effects across organization and industry levels of analysis.

At the organization level, firms may experience direct performance feedback during the execution of an innovative practice. In this context, performance feedback can be both a learning outcome and a learning input (Greve 2003b). This study focuses on performance information as a learning input (organization-level feedback) and investigates its effects on incremental changes of an innovative practice.

At the industry level, prior research (Baum and Ingram 1998, Greve 1995, Haunschild 1993) shows that organizations draw on vicarious learning by observing similar organizations to inform adjustments of their behavior—including decisions to adopt innovative managerial practices (Davis 1991, Kraatz 1998). Given the availability of relevant external information, these findings suggest that organizations may continue to use vicarious information to inform recurring incremental changes of the practice after its adoption.

The organizational literature acknowledges the multilevel nature of many organizational phenomena (House et al. 1995, Porter 1996) as well as the relevance of cross-level interaction (Brass et al., 2004). In their review of the multilevel research literature, Klein, Tosi, and Cannella (1999, p. 247) argued that "organizational change and innovation processes appear a promising target for multilevel theory and research." The empirical investigation of cross-level moderator effects in this study contributes to the more general work towards multilevel theories of organizations.

**RESEARCH SETTING**

The professional baseball industry provides a unique opportunity to investigate incremental learning after the adoption of an innovative practice among a set of profit-oriented organizations in a stable industry environment. During the 1920s and 30s, sixteen privately owned baseball organizations
competed in two separate leagues under virtually the same institutional rules and regulations. The regular season champions of each league competed in a playoff for the World Series title. Major-league baseball at the time was already recognized as the largest, best organized, and most business-like sports industry (New York Times, 3/3/27, p. 13).

In the early 1920s, Branch Rickey, general manager of the St. Louis Cardinals, conceived a structural HR innovation known as the farm team system (Anderson 1975, Golenbock 2000). Instead of acquiring major-league ready talent, Rickey would develop talent systematically by selecting and training a large pool of inexperienced, but talented players. In his own words:

“I said to myself that I could find other Hornsbys and other Frisches [both successful Cardinals players]. I would find them young. But I could find them and develop them. Pick them from the sandlots and keep them until they became stars. All I need was a place to train them.” (cf. Golenbock 2000, p. 87)

To develop this player pool, Rickey obtained control over a set of minor league clubs. Players signed special reserve clauses that prevented them from seeking employment at other clubs without their employer's consent. Control over minor league clubs enabled Rickey to integrate player selection, training, and promotion processes across clubs. New players entered the least skilled leagues (e.g., a D-league team) and progressed to more competitive teams based on performance. Ultimately, only a small percentage of players reached the major leagues, typically after playing several years in the minor leagues. The St. Louis Cardinals established the first farm team system in the early 1920s.

“[1925] Rickey now owned or controlled teams at every minor league level from Class D to Triple A. On a chalkboard in Rickey’s office was a list of every player in the organization. Rickey kept track of the stats of every one of them.” (Golenbock 2000, p. 99)

A few other clubs started implementing the practice after 1926; after 1932, the majority of teams followed; and by 1939, all teams had adopted the practice.

Industry histories, team histories, and trade journals provide rich anecdotal evidence that major league clubs faced substantial organizational learning challenges while implementing the farm team practice. The clubs had to learn how to evaluate players in earlier career stages, coordinate a larger staff of trainers and scouts, manage a larger pool of players with a broader range of skill levels, and integrate
selection and training processes across affiliated clubs (Anderson 1975, Burk 2001). These learning efforts led to continuing incremental change of specific traits of the innovation during the execution of the practice, including the learning outcome of interest in this study, namely farm team size (FT size).

Change in network size represented important decisions. A larger network implied a larger player pool with potentially positive effects on player development. At the same time, a larger farm team system required a higher resource commitment. The financial resources needed to acquire and support minor league farm teams were substantial, considering that major league clubs earned on average about $115,000 in annual profits during the 1920s and player payrolls ranged from $75,000 to $375,000 per year (Burk 2001, p. 3-4). The industry speculated, for example, that the New York Yankees paid $350,000 in 1931 to own the top-quality Newark Bears (New York Times, 11/13/31, p. 33).

In hindsight, baseball historians claim the farm team practice was a substantial innovation that “[…] brought about the greatest single change of this century in the business structure of the game” (Smith 2000, p. 200). Consequently, the decision to maintain, expand, or reduce farm team network size generated broad organizational implications and deserved substantial management attention during the execution of the practice. Figure 1 shows the continuing changes in network size for the different clubs.

**HYPOTHESES**

**Organization-Level Feedback Learning**

Theories of performance feedback learning imply that organizations tend to repeat and expand successful actions (Cyert and March 1963, Greve 2003b). This distinguishes them from theories of organizational change that emphasize inertia or simple momentum, in which an organization repeats what it has done before regardless of performance outcomes (Amburgey and Miner 1992, Kelly and Amburgey 1991). Selective repetition of behavior lies at the core of numerous learning models in the social sciences (Argote 1999, Levitt and March 1988) and has received broad empirical support related, for example, to acquisition behavior (Haunschild and Miner 1997), innovation adoption (Greve 1998b, Kraatz 1998), strategic reorientation (Audia et al. 2000, Lant et al. 1992), and network partner selection (Baum et al. 2005, Li and Rowley 2002). In general, the assumption that organizations are quite responsive to
performance feedback permeates the management literature, even though some researchers have questioned the generality of such claims and argued for the investigation of contingencies that may affect an organization’s ability and motivation to learn from feedback (Denrell and March 2001, Levinthal and March 1993, March et al. 1991, Staw et al. 1981).

Studies of the execution of R&D projects, for example, have offered only limited support for performance feedback effects. Observed effects were weaker than expected and contingent on specific conditions. Garud and Van de Ven (1992), for example, reported that negative performance feedback did not affect the likelihood of project changes—a finding they attributed to high levels of causal ambiguity and slack resources. Van de Ven and Polley (1992) showed that performance feedback learning occurred only during the later stages of the implementation of an R&D joint venture, consistent with arguments for an initial honeymoon period (Deeds and Hill 1999, Fichman and Levinthal 1991). Combined, these studies contradict the notion of a strong and uniform performance-feedback effect and indicate the need for further systematic investigations on when and how performance feedback affects organizational behavior during the execution of innovative projects or practices.

This study investigates the effects of recent performance feedback on the incremental change of a key innovation characteristic: the number of minor league clubs in a major league team’s farm team system. This type of decision shares some similarities with scope decisions related to mergers, acquisition, and divestitures (Johnson 1996). Compared to the present study, however, this stream of research tends to focus on non-incremental changes in organizational scope and heterogeneous acquisition targets. Studies of repeated acquisition behavior supported performance feedback learning—but found it contingent on acquisition salience (Haunschild and Miner 1997) and accumulated acquisition experience (Haleblian et al. 2006).

During the execution of the farm team practice, organizations continued to adjust the number of minor league clubs in their system (review Figure 1). Performance feedback learning requires the ability to observe one’s own prior actions and related performance changes (March and Olsen 1976). General studies of attention and salience support the notion that organizations usually attend closely to changes in
their performance (Ocasio 1997). Baseball clubs were constantly confronted with detailed performance feedback in the form of their team's field performance. They also had access to detailed information about their farm team activities, including the size of their network (Anderson 1975).

Performance feedback learning further requires the learning unit to believe that the focal decision will affect performance. Olson and Schwab (2000) showed that the farm team system substantially improved a club's win/loss ratio by approximately seven percent. Anecdotal evidence indicates that industry insiders believed in a strong performance effect of the farm team practice (Sporting News, 11/9/1931), increasing the likelihood that decision makers believed in a direct effect of network size on a club's field performance. A larger farm team system implied a larger internal labor market that would produce not only a greater number of eventual major league players, but also higher quality players due to higher selectivity in player promotions. In a follow-up study, Olson and Schwab (2006) reported that farm team systems indeed allowed major league clubs to add and retain higher quality batters and pitchers, which explained approximately 81 percent of the observed farm team performance effect. However, farm team size is not without cost: the larger the farm team system, the more resources it binds. This trade-off suggests an inverse U-shaped effect of network size on club performance.

Finally, for performance feedback learning to occur, the learning unit has to be able to control the future incremental changes. The documented acquisition activities of major league teams indicate that they controlled the incremental development of their farm team network (New York Times, 12/31/36, p. 10; 7/7/40, p. 2; 11/13/31, p. 33) even against the futile opposition of the baseball commissioner (Burk 2001, pp. 37, 44-45, 63-65).

In summary, both conceptual and empirical research suggest that recent performance feedback is a reasonable candidate for guiding network size adjustments. Performance improvement should motivate organizations to maintain existing collaborations or to seek additional collaboration partners, resulting in stable or increased network size in subsequent seasons. In contrast, if an organization experiences performance deterioration, it should consider terminating collaborations, which would reduce network size in future seasons. Thus, I hypothesize:
HI: During the execution of an innovative network practice, organization-level performance improvements will lead to an increase in an organization's network size, and performance deteriorations will lead to a decrease in network size.

Population-Level Vicarious Learning

Organizations do not learn in isolation. Instead, organizations often monitor the behavior of organizations in similar situations and try to learn from others’ experiences (Cyert and March 1963, Greve 1998b, Miner and Haunschild 1995). The selection of referent organizations seems to be dominated by considerations of knowledge relevance and information availability (Greve 1998a, Lant and Baum 1995, Porac et al. 1995). Emerging models of vicarious organizational learning (Greve 2003a, Miner and Anderson 1999) differentiate between sources of information (e.g., competitor, supplier, or customer), criteria for information relevance (e.g., reputation-based, frequency-based, or performance-based learning), and instruments of information transfer (e.g., directorate interlocks, alliances, or acquisitions). Related empirical research supports vicarious learning for acquisition behavior (Baum et al. 2000, Haunschild and Miner 1997, Hayward 2002), the adoption of practices (Davis 1991, Greve 1996, Kraatz 1998), and potential impact on organizational performance (Baum and Ingram 1998, Greve 1999).

In the baseball setting, information about competitors’ farm team network size was readily available due to the relatively small and stable number of well-defined competitors, detailed published news, and strong interorganizational ties (Burk 2001, pp. 64-65, Mann 1957, pp. 68-70). In the later 1930s, industry publications provided network structure information annually for all major league teams, including network size (Minor League Digest, 1936-1940). Thus, industry members knew who operated a farm team system and the size of competitors’ networks.

To learn from vicarious information, an organization must not only have access to external information, but must also consider the information relevant (Baum et al. 2000, Kraatz 1998). The high degree of homogeneity across clubs increased the likelihood that baseball managers assumed what worked for others would also work for their organization (Lee and Pennings 2002). Industry insiders considered the farm team practice highly performance relevant and keenly observed each other’s farm
team activities. After the St. Louis Cardinals won the World Series, for example, Sporting News (6/3/1926) discussed their farm system and speculated that performance improvements were due to the farm system or to the new coach. After the Cardinals won a second World Series, farm team practice was declared the key success factor (Sporting News, 11/9/1931; New York Times, 4/18/32, p. 22).

These considerations suggest that, for incremental changes of network size, vicarious learning is feasible. It is not, however, inevitable. A remaining learning challenge in the baseball setting, for example, is that network size was only one among numerous competitors' decisions that likely affected performance outcomes and some of these other decisions were more difficult for outsiders to observe. This challenges the attribution of overall performance impact to specific implementation choices, such as network size decisions (March and Sutton 1997, Repenning and Sterman 2002).

Vicarious learning research shows that firms have imitated technologies, organizational forms, or managerial practices frequently used by referent organizations (Abrahamson and Rosenkopf 1993, Greve 1996, Kraatz 1998). Such orientation on central tendencies in the behavior of others has also been supported for the determination of aspiration levels based on social comparisons (Greve 1998b). Orientation on population averages represent parsimonious models of vicarious learning that are consistent with arguments of bounded rationality and satisficing as explanation for organizations' constrained ability and motivation to engage in more elaborate forms of vicarious learning (March and Simon 1958).

Together, these considerations suggest that organizations may have used industry-level vicarious information to evaluate the appropriateness of their own farm team network’s size. As a starting point, this study tests a simple form of population-level vicarious observation: organizations may compare their network size to the predominant current network size of other similar organizations in the industry and adjust their network’s size towards the industry average.

**H2:** During execution of an innovative network practice, the difference between an organization’s network size and the average industry network size of other similar organizations will lead to subsequent changes of network size towards the industry average.
Cross-Level Interaction

The logic underlying H1 and H2 predicts that organization-level and population-level information independently influence incremental changes in network size. These hypotheses apply relatively well-established concepts of performance feedback learning and vicarious learning to an important but under-researched learning context: incremental changes during the execution of an innovative practice. The availability of both performance feedback at the organization level and vicarious information at the industry level raises the question not only of their relative impact, but also of their potential cross-level interactions. The organizational learning literature has long argued that such interactions are likely and not accounting for them can lead to severely underspecified models (Crossan et al. 1999, Cyert and March 1963, March 1991, 1999).

As previously noted, the debate about cross-level interactions has been mostly conceptual. Most studies that have captured both organizational experiential learning and population-level vicarious learning have not investigated potential cross-level interaction effects (Baum and Ingram 1998, Li and Rowley 2002). In the two studies that investigated interactions between information sources from the same level of analysis both substitutional and supplemental interactions received support (Haleblian et al. 2006, Haunschild and Beckman 1998)—hence, this study outlines the cross-level arguments supporting both types of interactions and formulates competing hypotheses in the next two sections.

Substitutional interaction. In the learning context studied, a substitutional interaction implies that both performance feedback and vicarious information affect incremental changes in network size, but their joint effect is weaker compared to the sum of their independent effects. Two prior studies have supported substitutional interactions between alternative sources from the same-level of analysis. For alternative industry-level sources, Haunschild and Beckman (1998) found substitutional interactions between board interlocks and membership in the Business Round Table on corporate acquisition behavior. For alternative organization-level sources, Haleblian et al. (2006) found a substitutional interaction between accumulated acquisition experience and early acquisition performance feedback (change in the acquirer’s stock price in response to acquisition announcement). Thus, both studies
support substitutional interactions between sources at the same level of analysis—but neither of the
studies captured cross-level interactions. The related conceptual research offers three mechanisms to
explain the presence of substitutional cross-level interactions: information redundancy, information cost,
and preference for internal over external information.

*Information redundancy.* If a decision is only influenced by novel or unique information, then
information from multiple sources has a substitutional effect if these sources provide redundant or
duplicate information (Wiener 1948). If an organization perceives the information from both sources as
completely equivalent, we would expect perfect substitution: the joint effect of information from both
sources is identical to the independent effect of each source. Haunschild and Beckman (1998), however,
argued that receiving similar consistent information from different sources can increase the confidence in
this information. If sources at different levels of analysis are perceived as more independent (Menon and
Pfeffer, 2003), information confidence effects become more likely. The combined information is
perceived as more relevant (stronger) than information from only one source—but weaker than the linear
addition of both sources’ independent effects. These considerations suggest a partially redundant effect.

*Information cost.* Organizations tend to curtail information search and information processing in
order to reduce associated costs and to avoid information overload (Simon 1955). Decision-making
research has supported such positive biases towards readily available information at the individual level
(Tyversky and Kahneman 1974) and at the organization level (Lant and Baum 1995, Ocasio 1997). For
example, organizations often engage in multiple simultaneous learning processes, but may curtail their
information search and information processing activities after obtaining information from one source that
satisfies their information needs (Cohen et al. 1972, March and Simon 1958). In that case, available
information from other sources does not affect decision outcomes, producing a substitutional interaction.
In the baseball setting, internal performance feedback and competitor network size information were
readily available. The interpretation of the available information, however, involved substantial
systematic efforts (New York Times, 02/03/1934, p. 16), which suggests opportunities for curtailed
information processing. For example, if an organization is predisposed to increase its network size by one
team and if this organization is already nearly convinced based on the interpretation of information from one source, any additional support based on analyzing information from a second source may be sufficient to make the decision; additional available supportive information would not produce an effect. In general, cross-level information searches and information interpretation imply broader and more costly activities, which should increase the potential for such curtailment. These conceptual considerations suggest substitutional effects for incremental learning from multi-level sources.

*Information preferences.* Organization-level internal information is typically more detailed, salient, and better understood compared to external information (Feldman and March 1981, Levinthal and March 1993). These characteristics of internal information facilitate analysis and interpretation and suggest a preference for internal over external information. On the individual level, higher levels of direct experience decrease the motivation of decision makers to engage in vicarious social comparison (Weiss et al. 1999). On the group level, Katz and Allen (1982) reported that a "not-invented-here" syndrome emerged during the implementation of R&D projects, in which project groups strongly preferred internal information over external ideas. In a detailed case study, Leonard-Barton (1992) showed how organization-level experiences can create core rigidities that decrease an organization's ability and willingness to learn vicariously. The baseball organizations possessed reliable and rich internal performance feedback. Thus, the notion of organizational preference for internal feedback information suggests a substitutional effect as available external information is ignored.

Information redundancy, information cost, and information preference emerge, then, as compelling arguments for cross-level substitutional effects. Data availability prevented a differentiation between these underlying processes. Thus, for an initial investigation, the following general hypothesis is tested:

**H3a:** *If an organization's network size is smaller compared to the average industry network size, organization-level performance improvements (deteriorations) will produce a weaker positive effect on subsequent increases (decreases) in the organization's network size.*

**Supplemental interaction.** Under certain conditions, learning research has also supported supplemental interactions between organization-level and population-level information sources, in which
both affect learning outcomes, but their joint effect is stronger than the sum of their independent effects. In the learning context of this study, the two most relevant underlying causal explanations are based on decision confidence and absorptive capacity.

*Decision confidence.* In addition to the earlier reported support for substitutional interactions, Haunschild and Beckman (1998) found one unexpected supplemental effect between two population-level sources: personal interorganizational relationships and population-level information broadcasts. The researchers argued that consistent information from multiple independent sources may increase decision confidence to a degree that the joint effect of information from two sources is stronger than the sum of their independent effects. As mentioned earlier, sources at different levels of analysis are likely to be perceived as more independent (Menon and Pfeffer 2003). Consequently, supplemental cross-level effects seem feasible. In the baseball setting, a supplemental interaction would translate into more substantial changes of farm team network size when direct performance feedback and vicarious observations both suggested an increase (or decrease) in network size.

*Absorptive capacity.* Alternative arguments for supplemental cross-level effects build on findings in the absorptive capacity literature, which show how accumulated organizational experiences can enable the identification and assimilation of valuable external information (Cohen and Levinthal 1990, Lane and Lubatkin 1998, Zahra and George 2002). Prior organizational learning research supports such a supplemental effect of internal experience. Tsai (2001), for example, found support for a supplemental effect of absorptive capacity (R&D intensity) and access to external information (network centrality) on business units engaged in R&D projects. For continuing learning after innovation adoption, Schwab, Olson and Miner (2002) reported that baseball team performance as a learning outcome was affected by both accumulated organization- and population-level farm team knowledge. They also found support for a supplemental cross-level interaction between these two information sources. Although most of the absorptive capacity literature assumes that an accumulation of internal knowledge is needed to identify and correctly interpret available external data, the researchers argued that it is just as plausible for externally acquired information to help an organization correctly interpret internal performance feedback.
It is also conceivable that the search and interpretation of information from sources at different levels of analysis could occur simultaneously or deeply interwoven without clear sequential order (Lant and Phelps 1999, March 1991). Lacking clear guidance from prior research, this study is neutral with regard to which information source provided the interpretative frame for the other. Instead, this study investigates the following hypothesis as an initial test for a general cross-level supplemental interaction effect:

\[ H3b: \text{If an organization's network size is smaller compared to the average industry network size, organization-level performance improvements (deteriorations) will produce a stronger positive effect on the subsequent increases (decreases) in the organization's network size.} \]

**METHODS**

The data set contains information from all sixteen U.S. major league baseball teams (j) for each of the seasons (t) from 1923 to 1940. The analyses in this paper pertain only to observations of organizations with farm teams, as only those organizations could adjust farm team network size. However, because all major league teams eventually adopted the practice, observations from all sixteen teams are included, which reduces potential sample selection biases.

The organization that innovated the practice, the St. Louis Cardinals, is excluded from the data set for three reasons. First, for several years the Cardinals had the only farm team system. Thus, no vicarious information was available to the Cardinals during earlier years. Second, the Cardinals’ substantial learning curve advantage may have limited their motivation and beliefs in the value of learning from others. Third, the Cardinals’ farm team system was unique; not only because of its first-mover advantages, but also in that it paid a ten percent commission on player sales to the general manager, Branch Rickey (Golenbock 2000, p. 247). The Cardinals produced far more players than needed to satisfy internal demand in order to profit from player sales. This strategy justified a far larger farm team size compared to other teams that later adopted the farm team practice (second movers). Indeed, at the end of the period, the Cardinals’ farm team system was twice the size of the largest second-mover and more than three times the size of the average second-mover. For these reasons, the study focuses on incremental learning of second-movers after their innovation adoption (N=70).
Dependent Variable

Change in Farm Team Network Size Next Season ($Y_{j,t+1}$) is the dependent variable in all models. Farm team network size is operationalized based on a club's number of affiliated minor league teams (mean=7.49; S.D.=3.70). Teams' affiliations are identified based on the Baseball Bluebook (1917-1940), the Minor League Digest (1936-1940), and an unpublished detailed list of farm team systems generated by a member of the Society of Baseball Research, Jerry Jackson. The combination of these resources provides a reliable measure despite rumors that—especially early on—the St. Louis Cardinals and others were trying to hide some of their farm links (New York Times, 4/18/32, p.22).

Independent Variables

Farm team practice. A major league club is considered as having executed the farm team practice when both of the following criteria are met: (1) the major league team was affiliated with at least two low-level minor league teams (league classifications B, C, or D) that were not playing in leagues at a similarly competitive level (e.g., both teams were not playing in B leagues); and (2) the major league team was affiliated with at least one high-level minor league club (league classifications AAA, A, or A-1). The different competitive levels of affiliated teams serve as a proxy for a hierarchical HR system that selected and developed players by systematically moving better players to more competitive teams. An effective system for developing players and improving overall team performance (Olson and Schwab 2000). Clubs that meet both of these criteria are assigned a dummy code of 1.

Performance feedback. During the regular season, each major league club received performance feedback as they played a relative stable number of about 22 games against each of their seven league competitors. Change in organizational performance is operationalized by the Change in Percentage of Games Won ($CPGW_{j,t}$) compared to the prior season. Given that the farm team practice focuses on player development, field performance seems the appropriate source of feedback information.

External network size comparison. Vicarious learning assumes that organizations tend to follow the examples set by referent organizations. Measures of central tendency are used as a simple proxy to capture farm team network size for the population of referent organizations--in this case, other
second-mover organizations currently executing the farm team practice. Subtracting the size of a team's farm network from the population's average network size results in the Difference in Population-Level Mean Network Size \((DPM_{j,t})\). For reasons previously noted, the first-mover (St. Louis Cardinals) is also excluded from the calculation of relevant population means. Additional analyses that included the Cardinals in the calculations of population means reduced variance explained, but did not change the general size and direction of regression coefficients of explanatory variables. In addition, the alternative measure Median Network Size is highly correlated with average network size \((r=.871; \ p<.001)\) and led to similar results.

**Control Variables**

Time dummy variables are included in all models to account for any season-specific fixed effects that could have influenced an organization's farm team size decisions. League Dummy \((LEA)\) accounts for any fixed differences between clubs in the American League versus the National League. Analyses also control for differences in Accumulated Farm Team Experience \((FTE_{j,t})\). The study uses the following proxies to control for differences in a club's resource endowment. Linear and non-linear effects of stadium Attendance \((ATT_{j,t})\) and \(ATT_{j,t} \times ATT_{j,t}\), respectively) and the team's success on the field \((PGW_{j,t})\) provide proxies for ticket and concession revenues. Ninety percent of a club's revenues came from gate receipts and stadium concessions because the period studied pre-dates significant revenues from radio and TV broadcasting rights (Leifer 1995). Including attendance and team success measures from seasons one or two years further in the past does not improve model fit or affect results. A dummy variable controls for any effects related to participation in Post-Season Play \((PSP_{j,t})\), which was a best-of-seven series between the regular season champions of the American League and the National League. Another dummy variable accounts for additional Financial Endowment \((FEN_{j,t})\) available to teams with wealthy owners, such as: “[...] multimillionaires Colonel Jacob Ruppert, the beer baron [New York Yankees]; William Wrigley, the chewing gum king [Chicago Cubs]; and Tom Yawkey, one of the richest men in the country [Boston Red Sox] [...]” (Golenbock 2000, p. 129)

The variable Change in Farm Team Network Size \((CFTS_{j,t-3})\) captures the difference between
farm team network size in (t) and (t-3) and controls for potential momentum effects (Amburgey and Miner 1992, Jansen 2004). In the fully specified model, $CFTS_{j,t-3}$ has a marginally significant positive effect ($b=.148; p<.10; \text{two-tailed}$). Momentum, however, explains less than one percent of the variance in network size change—an unexpectedly weak effect. Alternative operationalizations that control for changes since (t-1) or (t-2) led to similar results.

Analyses also include two proxies to control for changes in the pool of available minor league teams. The first measure $(MLT_t)$ captures the industry-wide number of minor league teams in farm team systems for every season. The second measure $(NML_t)$ captures the number of minor leagues operating in the U.S. for every season. The number of independent minor league teams decreased over time due to the diffusion of the farm team practice, increasing size of the farm team networks, and economic problems arising from the Great Depression (New York Times, 2/24/33, p.21; Burk, 2001, p. 58). All models include these two controls for effects of changes in the number of partners available.

Statistical Analyses

Regression analysis is used to test hypotheses. Robust standard errors are calculated using Huber and White variance estimators that control for team-specific serial correlation and heteroskedasticity (Rogers 1993, StataCorp. 2003, pp. 326-341).

RESULTS

Model Selection

Table 1 reports the means, standard deviations, and correlation coefficients for the main variables in the data set. Hierarchical regression analysis is used to evaluate the presence of the hypothesized interaction effect and to determine the appropriate model for hypothesis testing (Cohen and Cohen 1983). Model 7 in Table 2 shows that the addition of the interaction term Change in Percentage Games Won x Difference in Population Mean Network Size $(CPGW_{j,t} \times DPM_{j,t})$ significantly improves model fit ($\Delta R^2 = .103; F = 10.11; p<.01; \text{two-tailed}$). This finding supports the presence of the hypothesized interaction effect and suggests the use of Model 7 for hypothesis testing.
Organization-Level Feedback Learning (H1)

If performance improves during execution of a practice that had promised such improvement, the organization should consider extending the application of the practice. In the case of the farm team practice, H1 states that improvements in field performance compared to the prior season should cause the major league clubs to add more teams to the farm team network for the subsequent season. In the main effect Model 6, Change in Percentage Games Won exerts a positive, but only marginally significant, effect on next season’s change in network size (b=10.429; p<.10; one-tailed). The support for an interaction effect, however, suggests a conditional analysis based on Model 7.

In Model 7, the effect of performance improvements on the subsequent Change in Farm Team Network Size Next Season \(Y_{j,t+1}\) is captured by two variables: the main effect variable Change in Percentage Games Won and the interaction term Change in Percentage Games Won x Difference in Population Mean Network Size \(CPGW_{j,t} \times DPM_{j,t}\). A Wald test (Judge et al. 1985) indicates the significance of their joint effect (Wald test: \(b_1=b_3=0; F=4.79; p<.05; \) two-tailed). To determine the significance and direction of the effect in more detail, Eq. (2) for marginal changes in performance is derived from Eq. (1) that represents Model 7:

\[
\begin{align*}
Y_{j,t+1} &= b_0 + b_1 (CPGW_{j,t}) + b_2 (DPM_{j,t}) + b_3 (CPGW_{j,t} \times DPM_{j,t}) + \text{other controls} + \varepsilon_{j,t} \\
\frac{\partial Y_{j,t+1}}{\partial CPGW_{j,t}} &= b_1 + b_3 (DPM_{j,t}) = 15.832 - 7.512 (DPM_{j,t})
\end{align*}
\]

Estimates for marginal changes of Change in Percentage Games Won are calculated for moderator values at the mean, one standard deviation below the mean, and one standard deviation above the mean (Aiken and West 1991). Standard errors are reported in parentheses:

\[
\begin{align*}
\frac{\partial Y_{j,t+1}}{\partial CPGW_{j,t}} | DPM_{j,t} = -3.321 &= 40.78^{***} \quad (12.02) \quad (\text{FT Size} > \text{Population Mean FT Size}) \\
\frac{\partial Y_{j,t+1}}{\partial CPGW_{j,t}} | DPM_{j,t} = -.124 &= 16.76^{**} \quad (6.14) \quad (\text{FT Size} \approx \text{Population Mean FT Size}) \\
\frac{\partial Y_{j,t+1}}{\partial CPGW_{j,t}} | DPM_{j,t} = 3.073 &= -7.25 \quad (6.73) \quad (\text{FT Size} < \text{Population Mean FT Size})
\end{align*}
\]

The two significant regression coefficient estimates are positive (one-tailed). These results support H1 that performance improvements lead to subsequent increases in farm team network size. However, this effect is stronger when farm team network size is substantially larger than the average population network size. The effect of changes in performance is not significant for teams with farm
team sizes substantially smaller than the population average. The findings suggest that direct outcome information influences changes in how a practice is executed, but these effects are moderated by vicarious information obtained by observing the same implementation decision at other organizations. A major league club that experiences improvement of the win/loss ratio by 6.3 percent with a farm team network size equal to the population average will add another farm team for the next season.

Prior research reported that it took four years of implementation efforts before the farm team practice started to show positive performance effects (Olson and Schwab 2000). Analyses were performed to investigate to what degree organizations accounted for these initial performance lag effects in their performance-based adjustments of network size. If the teams were aware of this lag, performance improvements during the first three years after adoption should not have led to subsequent farm team network size increases or, at least, the effect should have been substantially weaker. The corresponding model, however, shows very similar results for the subset of clubs with less than four years of farm team experience (Model 8 in Table 2). The size, direction, and significance of regression coefficients for the performance feedback variables remain stable. The conditional analyses for reasonable moderator values for this subsample also show a pattern that resembles the results found in the full model (Model 7 in Table 2). Performance improvements have a significant positive effect on farm team network size change when a club’s farm team is equal or larger than the average population farm team network size of referent organizations. Although unexpected, these results are consistent with findings in studies of superstitious learning that document organizations’ tendencies to incorrectly attribute performance improvements to recent organizational actions (Abrahamson and Fairchild 1999, Repenning and Sterman 2002).

**Population-Level Vicarious Learning (H2)**

H2 hypothesizes that differences in farm team network size from the average network size in the industry lead to subsequent network size adjustments towards the industry mean. In the main effect Model 6 (Table 2), Difference in Population Mean Network Size \((DPM_{j,t})\) has a significant positive effect consistent with H2 \((b=0.528; \ p<.01; \ \text{one-tailed})\). The detected interaction effect in Model 7 suggests a conditional analysis. In the Model 7 regression equation, the effects of difference from the average
network size are captured by the variable Difference in Population Mean Network Size and the interaction term Change in Percentage Games Won x Difference in Population Mean Network Size 
\((CPGW_{j,t} \times DPM_{j,t})\). A Wald test indicates that the joint effect of these two variables is significant 
\((b_2=b_3=0; F=12.58; p<.001; \text{two-tailed})\). To determine the significance and direction of this moderated effect in more detail, Eq. (3) is derived from Eq. (1):

\[
(3) \quad \frac{\partial Y_{j,t+1}}{\partial DPM_{j,t}} = b_2 + b_3 (CPGW_{j,t}) = .682 - 7.512 (CPGW_{j,t})
\]

Again, estimates for marginal changes of Difference in Population Mean Network Size are calculated for reasonable moderator values to determine the direction of the effect based on Eq. (3):

\[
\begin{align*}
[\partial Y_{j,t+1}/\partial DPM_{j,t} | CPGW_{j,t} = -.066] &= 1.17***(.218) \quad \text{(Recent Performance Deterioration)} \\
[\partial Y_{j,t+1}/\partial DPM_{j,t} | CPGW_{j,t} = .006] &= .64**(.163) \quad \text{(No Recent Change in Performance)} \\
[\partial Y_{j,t+1}/\partial DPM_{j,t} | CPGW_{j,t} = .077] &= .10 (.250) \quad \text{(Recent Performance Improvement)} 
\end{align*}
\]

Two significant regression coefficient estimates are positive (one-tailed) and support H2. Based on vicarious observations, organizations tend to adjust their farm team network size towards the population average, but this effect is not significant in organizations that have recently experienced substantial performance improvements. With no recent change in performance, however, a major league club with a farm team system that is 1.5 teams smaller than the industry average will add another minor league team to its farm team system.

**Cross-Level Interaction (H3)**

The hierarchical regression analysis indicates support for the presence of an interaction between organization-level performance feedback and population-level vicarious network size comparisons (Model 7: \(\Delta R^2=.103; F=10.11; p<.01; \text{two-tailed}\)). The respective interaction term Change in Percentage Games Won x Difference in Population Mean Network Size \((CPGW_{j,t} \times DPM_{j,t})\) is negative and significant \((b=-.7.512; p<.01; \text{one-tailed})\).

This finding supports the hypothesized substitutional effect (H3a) and rejects the hypothesized supplemental effect (H3b). Figure 2 depicts the interaction effect. The incline of the plane decreases for higher values of both independent variables. It also shows how change in the percentage of games won
exerts a strong positive effect for organizations whose networks are already larger than the population average. At organizations with networks smaller than the population average, however, the variable has no effect. At these organizations, change in network size is dominated by a strong adjustment to the population mean and this effect is stronger for organizations in performance decline. When both performance feedback and comparison to the population mean suggest a network size increase, the increase occurs—but the joint effect is substantially smaller than the linear addition of their independent effects, which indicates a strong substitutional interaction effect.

Additional Analyses

This section reports findings of several additional analyses that probe the robustness of the reported findings. Detailed results are available upon requests from the author.

**Starter effect.** Adjustments toward the population mean could be the result of recent adopters’ relatively small network size and, thus, higher likelihood to increase network size. Adding the interaction between Difference in Population Mean \((DPM_{jt})\) and years of Accumulated Farm Team Experience \((FTE_{jt})\) to the main effect Model 6 in Table 2, however, does not improve model fit \((\Delta R^2=.0003; F=.03; p=.871;\) two-tailed\). This result indicates that adjustments towards the population mean are independent from accumulated experience and time since adoption.

**Time effects.** All models include year dummies to control for fixed difference between years. An additional, split-group comparison between earlier and later period observations reveals that the regression coefficients of the variables of interest remain in the same direction. The small sample size of the two split groups calls for a cautious interpretation, but results indicate the general robustness of reported findings for potential changes in practice legitimacy and industry-level experience over time.

**Team effects.** Model 9 in Table 2 probes for any remaining fixed differences between teams. Team dummy variables increase variance explained by 16.4 percent, but even this very restrictive model does not fundamentally change the size, direction, or significance of the regression coefficients for the variables of interest.

**Network size.** The reported models did not control for a major league team's farm team network
size and farm team network size squared. Their high correlation with Difference in Population Mean Network Size \((DPM_{j,t})\) \((r=-.860\) and \(r=-.873\), respectively) creates problems for the interpretation of its conditional effect. Adding these two controls to the full model, however, does not affect the results related to the other independent variables and substituting them for \((DPM_{j,t})\) reduces model fit by 2.7 percent variance explained. Thus, network size differences do not offer a superior explanation compared to vicarious learning oriented on population means.

**Accumulated Experience.** In the full model, accumulated farm-team-specific experience \((FTE_{j,t})\) has a marginally significant positive effect \((b=.417; p<.10; \text{two-tailed})\) and explains 4.1 percent of the variance. This result is consistent with arguments that accumulated farm team experience increased the propensity to expand farm team size. Adding an interaction term between accumulated experience and performance feedback to Model 6 (Table 2) significantly improves model fit \((\Delta R^2=.039; F=12.93; p<.01; \text{two-tailed})\). That improvement, however, is significantly smaller compared to Model 7, which added the hypothesized interaction with vicarious information \((\Delta R^2=.103; F=10.11; p<.01; \text{two-tailed})\). If both interaction terms are included simultaneously, only the interaction between performance feedback and vicarious information is significant \((b=-7.109; p<.05; \text{two-tailed})\). Adding a similar interaction between accumulated experience and difference to population mean network size did not improve model fit significantly \((\Delta R^2=.0004; F=.03; \text{n.s.; two-tailed})\). These findings indicate that accumulated farm team experience and related absorptive capacity arguments do not represent a superior explanation for the observed effects.

**DISCUSSION**

Despite a long history of organizational learning research, substantial gaps in our understanding of this phenomenon persist. This study explores a particular prominent void—potential cross-level interactions between organization-level performance feedback and population-level vicarious observations. In the process, this study shows how recent performance changes guide subsequent adjustments of an innovative managerial practice captured by changes in farm team network size (H1).
At the same time, vicarious observations lead organizations to adjust their farm team network size towards the population average (H2). Findings further indicate support for the presence of a substitutional interaction between organization-level performance feedback and population-level vicarious network size comparisons (H3a). The following sections outline the main theoretical and practical implications of these findings in more detail.

**Organization-Level Feedback Learning**

Support for the first hypothesis is consistent with the well-established general notion of trial-and-error learning in the organizational literature (Cyert and March 1963, Lave and March 1992). The robust moderated effect of performance feedback extends prior research in several important ways.

Performance-feedback learning forms the core of many models of organizational learning, but that has been empirically tested in relatively few studies. Prior research that investigated the effects of performance feedback either did not account for interactions with information from other information sources (Baum et al. 2000, Haunschild and Miner 1997, Li and Rowley 2002) or focused on same-level information sources (Haleblian et al. 2006). Despite their differences, these empirical studies support the notion of performance-feedback learning for the context of repeated acquisitions and repeated collaborations – consistent with the finding for repeated adjustments of network size.

Studies of R&D projects, however, reported no responsiveness to performance feedback during early project stages—which has been attributed to high-levels of ambiguity. In contrast, the findings of this study indicate that organizations responded to changes in performance during early stages of practice execution. The baseball organizations did not even allow sufficient time for the innovative practice to affect performance, which led to superstitious learning. Optimistic industry beliefs may have encouraged superstitious attributions of performance improvements. Anecdotal evidence shows that after some initial uncertainty (Sporting News, 6/3/1926), industry insiders shared a strong belief in the positive performance effect of the farm team practice (Sporting News, 11/9/1931)—leading to what the New York Times called "farm fever" (1/14/37, p. 29). The observed superstitious learning tendencies during the execution of a practice represent an extension of prior research of bandwagon effects focused on the
adoption of innovative practices (Abrahamson and Rosenkopf 1993, Fiol and O'Connor 2003) and studies of attribution errors focused on general changes of core business processes (Repenning and Sterman 2002).

The reported lack of responsiveness to early performance feedback during R&D projects may represent learned behavior to avoid superstitious learning and premature false-negative decisions. In the R&D studies (Garud and Van de Ven 1992, Van de Ven and Polley 1992), the large biomedical companies had substantial experience with executing innovative R&D projects. The baseball organizations lacked similar experience in the execution of innovative practices and therefore may have been more prone to engage in superstitious performance-feedback learning. In addition, the biomedical companies and baseball organizations faced very different types of ambiguity. The biomedical companies lacked reliable performance-feedback information. The developed products were years away from affecting organizational outcomes. In contrast, the baseball teams executing the innovative practice were constantly confronted with reliable on-the-field performance information. Player development had obvious lag times, but the farm team practice also offered potential instantaneous advantages—like access to more minor league players (labor pool effects) and increased performance pressure for current major league players (tournament effects) (Olson and Schwab 2006). Thus, baseball organizations did not face ambiguity related to the reliability of the performance information. Instead, they faced ambiguities related to the correct causal attribution of changes in performance to a specific prior organizational action. The empirical findings of this study indicate that reliable performance feedback information does not protect against superstitious learning—quite to the contrary, in settings with substantial causal ambiguity the availability of reliable performance feedback may trigger superstitious learning activities. These challenges of causal attribution highlight an important field for future performance-feedback research. Combined, the support for a moderated instead of an unconditional performance-feedback effect and the unexpected finding of strong superstitious learning tendencies illustrates the benefits of more fine-grained models of learning during innovation execution.
Population-Level Vicarious Learning

The relevance of population-level vicarious information for the decision to adopt an innovative practice has been widely accepted in the management literature (Miner and Anderson 1999, Nelson and Winter 1982, Rogers 1983). The availability of internal performance feedback after adoption, however, substantially changes the learning context. Although some researchers have argued that a bias towards internal information sources tends to crowd out external-oriented learning efforts (Burgelman 1994, Leonard-Barton 1992), findings in the current study clearly indicate that the availability of direct performance feedback after the adoption of an innovation did not lead organizations to disregard external vicarious information. Instead, industry-level vicarious observations of similar referent organizations continued to affect incremental changes of how the innovative practice was implemented.

General support for an effect of vicarious observations raises the question as to whether the observed effect of broad industry measures of central tendencies is better explained by more focused vicarious learning activities. Prior research has supported more focused referent selection based on information availability (Lant and Baum 1995), organizational similarity (Greve 1998a, Porac et al. 1995), organizational success (Burns and Wholey 1993, Haunschild and Miner 1997), and organizational status (Podolny and Stuart 1995). In the baseball context, high levels of industry transparency and organizational homogeneity make more restrictive referent selection based on information availability or organizational similarity unlikely. More restrictive selection based on success or status, however, present viable alternatives. Additional models, however, showed that orientation on clubs with a winning season record led to similar results for the variables of interest, but reduced model fit compared to orientation on the network size of all second movers. These results are also robust when restricting this model to years when at least two teams with farm team systems had winning records or when including the St. Louis Cardinals in the calculation of the average network size for successful teams. Hence, orientation on successful teams is not a better explanation compared to orientation on the average network size of all second-movers.

Alternatively, second-movers may have imitated the network size of the industry leader at that
time: the New York Yankees (Burk 2001, Dewey and Accocella 2005), who adopted the farm team practice in 1929 (New York Times, 1/11/29, p.22; New York Times, 11/13/31, p.33). Again, models probing for second-mover orientation on the Yankees did not improve variance explained. Thus, orientation on the industry leader does not offer a superior explanation for observed effects. Similarly, orientation on the innovator and first-mover (St. Louis Cardinals) did not improve model fit, which discredits first-mover referent as an alternative explanation.

Combined these additional models indicate that substantive findings of the study are robust for alternative, more restrictive referent group selection. The reported findings in this paper are based on the most parsimonious model, that is, orientation on second-movers in general. The high correlations between the network size of different referent groups in this setting (range: $r=.772$ to $r=.961$) limited opportunities to determine their relative importance and indicate that organizations using different referent groups received quite similar information. This finding supports the argument that the more transparent the setting and the more homogenous potential referents--the less impact has referent selection. Future investigations in settings with less homogenous competitors and in less transparent industries are encouraged to substantiate this claim and to better understand the contingencies affecting referent selection and related learning effects.

**Cross-Level Interactions**

Findings from the investigation of cross-level moderating effects show that incremental change was influenced by information available at both organization and industry levels. Organizations appear to combine information received from different levels of analysis, and this combination leads to a substitutional interaction in which consistent information from both information sources has a weaker effect compared to the linear addition of their independent effects. The relatively strong interaction effect discovered advocates the value of using multilevel learning frameworks to understand incremental learning after the adoption of an innovative practice.

The study introduced several potential underlying explanations for support of the hypothesized substitutional effect, including information redundancy, information cost, and preference for internal
information. The available data prevented any clear differentiation between their relative importance, but revealed some additional details about the nature of the substitutional effect. The study finds that organizations with farm team systems equal to or larger than the population average respond more strongly to recent direct performance feedback. Perhaps the clubs considered size increases beyond "industry wisdom" riskier, causing the organizations to attend more closely to internal performance feedback. Substantial upward size deviations from others in the industry may have led to perceptions that information about the implementation at other organizations was less relevant and valuable. In contrast, organizations that experienced recent declines in performance oriented themselves more on the network size of other organizations. Negative performance feedback may lead an organization to question both its ability to master the innovative practice as well as its ability to learn from its own performance feedback. Such uncertainty may lead organizations to rely more on simple vicarious information, such as the network size of similar competitors. Available positive feedback, in contrast, should reduce an organization's orientation towards simple vicarious information because the organization is more confident about its own implementation abilities.

This more differentiated understanding represents an important step forward and away from arguments for uniform and independent effects of performance feedback and vicarious observations. Results also contradict the simple notion of a general organizational preference for familiar internal information (Katz and Allen 1982, Weiss et al. 1999). Instead the study complements findings by Menon and Pfeffer (2003), who reported that under certain conditions organizations favor vicarious information. In their two case studies, organizations perceived external information as unique and valuable, even though it was far less rich compared to familiar internal knowledge. They argued that the effort involved in collecting and interpreting the external information led to perceptual biases favoring it. In addition, the familiarity with the internal information led to a shared recognition of its limitations and flaws. In the baseball setting, industry transparency discards positive perception biases for external data related to substantial data collection efforts. The other arguments for perceptual biases, however, cannot be ruled out. Independent of underlying explanations, the study’s findings indicate: organizations experiencing
performance deterioration lost confidence in their ability to learn from direct performance feedback and tended to orient incremental change decisions more on available external information. This interpretation is also consistent with studies of more fundamental organizational change that reported how moderate performance problems tend to stimulate external searches (Greve 1998b, Lant et al. 1992).

**Limitations and Future Research**

The clearly nested structure of production in the baseball industry and the availability of information at the levels of player, organization, league, and industry represents a setting well-suited for multilevel research (Golf and Tollison 1990, Wolfe et al. 2005). The use of proxies to capture learning inputs and outcomes is consistent with contemporary learning research (Argote 1999), but should encourage and guide more elaborate future research efforts that capture cross-level learning more directly. This future research should also pay careful attention to the factors that likely supported learning activities in the baseball setting. For example, high-levels of industry transparency, organizational homogeneity, and external visibility of the practice clearly supported vicarious learning. Similarly, the innovative practice’s strong impact on organizational performance and the reliable performance feedback information supported trial-and-error learning. These considerations suggest that findings should generalize to settings with similar characteristics, like other sport industries, movie productions, or the advertisement industry. The findings may also generalize to learning within large organizations that operate multiple, partially independent (but homogenous) organizational units, such as the military, hospitals, or franchise systems. Superordinate institutions, like the franchisor, can create levels of transparency and homogeneity among units to support learning from both direct and indirect experience.

Schwab, Olson and Miner (2002), in a related study, report a supplemental cross-level interaction between accumulated organization-level and accumulated industry-level farm team experience. Hence, supplemental cross-level interactions between broad experience measures affecting higher-level learning outcomes (e.g., organizational performance) can coexist with substitutional effects between narrow information sources on such lower-level incremental change decisions as network size adjustments. In general, this emerging support for complex multilevel interactions suggests moving beyond investigating
the effects of specific information sources only in isolation. Instead, such studies need to be complemented with an understanding of related cross-level interactions despite the substantial challenges of multilevel research (Klein and Dansereau 1994). The current study contributes to the development of more detailed multilevel learning models and provides a better empirical footing for the associated emerging discourse.

**CONTRIBUTIONS**

This study supports the importance of both performance feedback information at the organization level and vicarious observations at the industry level for the incremental change of innovative practices during their execution. Recognizing opportunities for incremental change and systematically exploiting available internal and external information to inform these change decisions promises a source of sustainable competitive advantage (March 1991). To exploit these opportunities, we need more fine-grained models of learning after innovation adoption, models that account for learning from both organization and population-level information sources—and models that better address superstitious learning tendencies.

Beyond contributions to performance feedback and vicarious learning research, a primary objective of this study was the more general investigation of potential interaction effects between information sources at different levels of analysis. The support for substitutional interdependence between organization-level performance feedback and vicarious observations of other organizations on incremental change of network size extends the organizational learning research and literature. The interaction effect accounted for 10 percent of the variance explained, an effect that is both statistically and practically significant. These results substantiate conceptual studies that for decades have argued for the relevance of such cross-level learning interactions (Cyert and March 1963, March 1991, Miner and Haunschild 1995) and simulation studies that indicated their general feasibility (Carley 1999, Lounamaa and March 1987). The support demonstrated for a substitutional relationship in this study contributes to this so far mostly conceptual debate, and takes an important step towards the development of more comprehensive multilevel models of organizational learning. Such multilevel models with well-
developed conceptual foundations and associated analytical methodologies promise important advances for both research and practice.
**REFERENCES**


Jackson, J. List of baseball club affiliations. Unpublished data.


*Minor League Digest*. 1936-1940. Heilbroner Baseball Bureau, Fort Wayne, IN.


*Sporting News*. 1886-present. Sporting News Publications, St. Louis, MS.

StataCorp. 2003. *Stata Statistical Software: Release 8.0*. Stata Corporation, College Station, TX.


### TABLE 1

Means, Standard Deviations, and Correlations for Dependent Variables and Independent Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>S</th>
<th>D</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in Farm Team Network Size Next Season (Yj,t+1)</td>
<td>0.83</td>
<td>3.27</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>League Dummy (LEA)</td>
<td>0.41</td>
<td>0.50</td>
<td>0.053</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attendance (ATTj,t)</td>
<td>525.75</td>
<td>232.48</td>
<td>0.072</td>
<td>0.375</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attendance Squared (ATTj,t x ATTj,t)</td>
<td>329685</td>
<td>276504</td>
<td>0.071</td>
<td>0.376</td>
<td>0.981</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage Games Won (PGWj,t)</td>
<td>0.52</td>
<td>0.10</td>
<td>-0.090</td>
<td>-0.077</td>
<td>0.056</td>
<td>0.068</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Season Participation (PSPj,t)</td>
<td>0.17</td>
<td>0.38</td>
<td>0.001</td>
<td>0.002</td>
<td>0.011</td>
<td>-0.031</td>
<td>0.604</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial Endowment Dummy (FENj,t)</td>
<td>0.23</td>
<td>0.42</td>
<td>-0.034</td>
<td>-0.182</td>
<td>0.224</td>
<td>0.193</td>
<td>0.535</td>
<td>0.384</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minor League Teams in Farm Team Systems (MLTt)</td>
<td>111.46</td>
<td>51.54</td>
<td>-0.174</td>
<td>0.215</td>
<td>0.265</td>
<td>0.261</td>
<td>-0.087</td>
<td>-0.034</td>
<td>-0.053</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Minor Leagues (NMLt)</td>
<td>32.04</td>
<td>8.12</td>
<td>-0.168</td>
<td>0.172</td>
<td>0.314</td>
<td>0.298</td>
<td>-0.119</td>
<td>-0.064</td>
<td>-0.104</td>
<td>0.928</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Accumulated Farm Team Experience (FTEj,t)</td>
<td>4.01</td>
<td>2.81</td>
<td>-0.175</td>
<td>-0.431</td>
<td>-0.175</td>
<td>-0.190</td>
<td>0.313</td>
<td>0.215</td>
<td>0.046</td>
<td>0.179</td>
<td>0.182</td>
<td></td>
</tr>
<tr>
<td>Change in Farm Team Network Size (CFTSj,t)</td>
<td>4.63</td>
<td>3.92</td>
<td>-0.173</td>
<td>0.080</td>
<td>0.078</td>
<td>0.070</td>
<td>-0.195</td>
<td>-0.093</td>
<td>0.043</td>
<td>0.241</td>
<td>0.189</td>
<td></td>
</tr>
<tr>
<td>Change in Percentage Games Won (CPGWj,t)</td>
<td>0.00</td>
<td>0.07</td>
<td>0.131</td>
<td>0.052</td>
<td>-0.028</td>
<td>0.354</td>
<td>0.224</td>
<td>0.043</td>
<td>-0.079</td>
<td>-0.103</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size of Successful Teams (DPMSj,t)</td>
<td>-0.12</td>
<td>0.70</td>
<td>0.370</td>
<td>0.244</td>
<td>0.134</td>
<td>0.160</td>
<td>-0.121</td>
<td>-0.163</td>
<td>-0.196</td>
<td>0.001</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size (DPMj,t)</td>
<td>-0.10</td>
<td>1.72</td>
<td>-0.060</td>
<td>-0.103</td>
<td>-0.039</td>
<td>-0.028</td>
<td>-0.083</td>
<td>-0.013</td>
<td>0.057</td>
<td>-0.185</td>
<td>-0.225</td>
<td></td>
</tr>
<tr>
<td>Difference in Industry Leader Network Size (DILj,t)</td>
<td>4.20</td>
<td>4.16</td>
<td>0.180</td>
<td>0.317</td>
<td>0.288</td>
<td>0.300</td>
<td>-0.150</td>
<td>-0.199</td>
<td>0.613</td>
<td>0.621</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in First-Mover Network Size (DFMj,t)</td>
<td>16.56</td>
<td>7.53</td>
<td>0.071</td>
<td>0.325</td>
<td>0.308</td>
<td>0.307</td>
<td>-0.101</td>
<td>-0.085</td>
<td>-0.113</td>
<td>0.868</td>
<td>0.799</td>
<td></td>
</tr>
<tr>
<td>Difference in First-Mover Network Size x Change in Percentage Games Won (DFMj,t x CPGWj,t)</td>
<td>0.05</td>
<td>1.28</td>
<td>0.089</td>
<td>0.054</td>
<td>0.032</td>
<td>0.040</td>
<td>0.315</td>
<td>0.144</td>
<td>0.064</td>
<td>-0.080</td>
<td>-0.080</td>
<td></td>
</tr>
<tr>
<td>Change in Farm Team Network Size (CFTSj,t)</td>
<td>-0.209</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in Percentage Games Won (CPGWj,t)</td>
<td>-0.031</td>
<td>0.008</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size (DPMj,t)</td>
<td>-0.331</td>
<td>-0.573</td>
<td>-0.075</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Percentage Games Won (DPMj,t x CPGWj,t)</td>
<td>-0.005</td>
<td>-0.021</td>
<td>0.163</td>
<td>0.143</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size of Successful Teams (DPMSj,t)</td>
<td>-0.281</td>
<td>-0.598</td>
<td>-0.056</td>
<td>0.961</td>
<td>0.079</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Industry Leader Network Size (DILj,t)</td>
<td>-0.055</td>
<td>-0.035</td>
<td>0.172</td>
<td>0.080</td>
<td>0.928</td>
<td>-0.009</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in First-Mover Network Size (DFMj,t)</td>
<td>-0.017</td>
<td>0.037</td>
<td>-0.082</td>
<td>0.429</td>
<td>-0.072</td>
<td>0.476</td>
<td>-0.153</td>
<td>0.874</td>
<td>-0.099</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in First-Mover Network Size x Change in Percentage Games Won (DFMj,t x CPGWj,t)</td>
<td>-0.042</td>
<td>0.027</td>
<td>0.917</td>
<td>-0.093</td>
<td>0.252</td>
<td>-0.101</td>
<td>0.297</td>
<td>0.115</td>
<td>0.942</td>
<td>-0.086</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N = 70
Two-tailed tests:
† p < .10
* p < .05
** p < .01
*** p < .001
## TABLE 2

OLS Regressions on Change in Farm Team Network Size For Next Season (Y\(_{j,t+1}\))

Controlling for Lack of Independence between Observations of the Same Team

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.000</td>
<td>0.851</td>
<td>*</td>
<td>7.383</td>
<td>*</td>
<td>7.192</td>
<td>†</td>
<td>9.333</td>
<td>†</td>
</tr>
<tr>
<td>Team Dummies</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>League Dummy (LEA)</td>
<td>0.142</td>
<td>-0.473</td>
<td>0.142</td>
<td>-0.573</td>
<td>-0.747</td>
<td>-0.482</td>
<td>-0.795</td>
<td>0.473</td>
<td>0.851</td>
</tr>
<tr>
<td>Attendance (ATT(_{j,t}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attendance Squared (ATT(<em>{j,t}) x ATT(</em>{j,t}))</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Post Season Participation (PSP(_{j,t}))</td>
<td>1.124</td>
<td>1.124</td>
<td>1.136†</td>
<td>1.286</td>
<td>1.449</td>
<td>1.918†</td>
<td>1.493</td>
<td>1.216</td>
<td>2.136</td>
</tr>
<tr>
<td>Financial Endowment Dummy (FEN(_{j,t}))</td>
<td>-0.231</td>
<td>-0.231</td>
<td>-0.309</td>
<td>0.094</td>
<td>1.133</td>
<td>1.463</td>
<td>2.629</td>
<td>0.855</td>
<td></td>
</tr>
<tr>
<td>Minor League Teams in Farm Team Systems (MLT(_{j,t}))</td>
<td>-0.008</td>
<td>-0.007</td>
<td>-0.005</td>
<td>-0.031</td>
<td>-0.045*</td>
<td>0.076*</td>
<td>-0.104</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Minor Leagues (NML(_{j,t}))</td>
<td>-0.069</td>
<td>-0.071</td>
<td>-0.061</td>
<td>0.101</td>
<td>0.165</td>
<td>0.055</td>
<td>0.253</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accumulated Farm Team Experience (FTE(_{j,t}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in Farm Team Network Size (CFTS(_{j,t}))</td>
<td>-0.258†</td>
<td>0.087</td>
<td>0.148†</td>
<td>0.459**</td>
<td>0.230</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in Percentage Games Won (CPGW(_{j,t}))</td>
<td>10.429</td>
<td>15.832*</td>
<td>17.844*</td>
<td>16.225†</td>
<td>18.447*</td>
<td>16.225†</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size (DPM(_{j,t}))</td>
<td>0.528**</td>
<td>0.682***</td>
<td>1.429***</td>
<td>1.107**</td>
<td>1.429***</td>
<td>1.107**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Population Mean Network Size x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in Percentage Games Won (DPM(<em>{j,t}) x CPGW(</em>{j,t}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R2</td>
<td>0.1600</td>
<td>0.2104</td>
<td>0.2104</td>
<td>0.2109</td>
<td>0.2786</td>
<td>0.3833</td>
<td>0.4863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ R2</td>
<td>0.0504</td>
<td>0.0000</td>
<td>0.0005</td>
<td>0.0677</td>
<td>0.1047</td>
<td>0.1039</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald F-Test for added variables</td>
<td>4.83**</td>
<td>7.18**</td>
<td>0.77</td>
<td>4.58†</td>
<td>4.75*</td>
<td>10.11**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald F-test variables incl. Change in Percentage Games Won (CPGW(_{j,t}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald F-test variables incl. Difference in Population Mean Network Size (DPM(_{j,t}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald F-test interaction term</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>35</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors reported in parentheses account for potential lack of identical distribution of residuals across observations. In addition, analyses control for lack of error independence for observations of the same major league team (StataCorp., 2003). Using the median population-level Farm Team Network Size instead of the mean lead to similar result patterns, but slightly less variance explained. Model 8 contains only observations for organizations with three or less years of farm team experience. Model 9 includes fifteen team dummy variables.
Learning from Multilevel Sources

Figure 1

Farm Team Network Size of Individual Major League Clubs

Note: Figure adopted from Schwab et al. (2002).
**Figure 2**

*Interaction between Difference to Population Mean Network Size (DPM\(_{jt}\)) and Change in Percentage Games Won (CPGW\(_{jt}\))*