Industry-Level Variability of Learning Outcomes from the Accumulation of Implementation Experience with an Administrative Innovation

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This paper tests theory about industry-level variability in learning outcomes following the implementation of a major administrative innovation. We challenge the intuition that early periods will be marked by more variation than later periods. We propose that ongoing organizational learning from vicarious experience, learning from direct experience and learning in the presence of population-level learning can create greater industry-level variation in learning outcomes. Contingency factors that can shape variability in learning outcomes include the use of varied imitation rules, deliberate innovation, interactions between innovation features and interactions between levels of learning. We test our framework using data on the farm-system, a massively impactful administrative innovation implemented in the U.S. baseball industry starting in the 1920s. Results show greater industry-level variation in a key innovation feature in the later period of accumulated implementation experience, consistent with our theory. Later period industry-level performance variation was lower, however. We speculate that this pattern is consistent with the potential impact of selective vicarious learning and deliberate experimentation. These contingency factors can generate divergence of an innovation feature coupled with improvement and convergence of performance. Understanding contingency factors for industry-level variability is important given the key role of industry variability in industry-level adaptation.

Key words: Industry-level variability of learning outcomes, management innovation, organizational learning, population-level learning

Several major theoretical traditions imply that the accumulation of industry experience with an innovation will typically lead to more similarity of a diffusing innovation and its impact. We label this widespread intuition the generic *convergence assumption.* Basic evolutionary models of industry change posit that after an innovation is first implemented, industry-level selection processes will produce convergence in how the innovation is enacted and its survival impact (Aldrich and Ruef, 2006). Iconic work on technology evolution describes early variation of an innovation, followed by convergence to more homogenous product features, and technology standards that lead to greater difficulty in sustaining performance variation (Utterback and Abernathy, 1975; Nelson and Winter, 1982; Tushman and Anderson, 1986). Classic institutional theory emphasizes how mimetic, coercive, and normative pressures lead populations of organizations to move from divergent activities, forms, and norms toward greater homogeneity (DiMaggio and Powell, 1983; Tolbert and Zucker, 1983; Scott, 2008), while contemporary work offers more nuanced insight into specific processes (Westphal, Gulati, and Shortell, 1997; Garud, Jain, and Kumaraswamy, 2002; Kennedy and Fiss, 2009). Historically the key differences between many theoretical schools come from their different accounts of why convergence should occur. This paper proposes instead that convergence may not occur at all, and divergence can arise from the accumulation of industry-level implementation experience, even in the absence of external shocks or new competitors.

Specifically, we propose that ongoing organizational learning processes can generate industry-level variability in innovation features and organizational performance outcomes after the sustained implementation of a major administrative innovation in an industry. We theorize that three mundane organizational learning processes—vicarious learning, learning from direct experience, and learning in the presence of population-level learning activities—will generate the greater variability in industry-level outcomes. We draw on prior theory to emphasize four potential drivers of variability (Miner, Haunschild, and Schwab, 2003): inconsistent vicarious learning modes (Greve, 1996, 1998; Miner and Raghavan, 1999), challenges to learning from direct experience (Levinthal and March, 1993), interactions between innovation features (Levinthal, 1997), and interactions between levels of learning (Anderson, 1999; Haunschild and Sullivan, 2002; Schwab, 2007). We focus on factors that should enhance variability as a pathway to building explicit contingency theories of when industry-level convergence or divergence will dominate.

Understanding determinants of industry-level variability in learning outcomes is important for understanding of industry-level adaptation and change (March, 1991; Levinthal, 1998; Aldrich and Ruef, 2006). Variation within a system can represent the reservoir of behaviors that will allow it to survive exogenous shocks and threats or can provide unplanned novel behavior that creates new sources of value (Astley, 1985). Variability in practices can also offer the pool of actions from which most adaptive actions can be selected, permitting population-level increases in fitness and long term survival, using evolutionary terms (Aldrich and Ruef, 2006).

We test our theories in a setting where a major administrative innovation was eventually implemented by all industry participants with considerable impact on the performance of the implementing organizations. The setting permits us to examine the industry-level variability in an important innovation feature and organizational outcomes for a consistent set of organizations as the industry accumulated implementation experience.

Our results reveal more, not less, variability in a key *administrative innovation feature* as the industry accumulated more implementation experience, consistent with our theoretical framework. In contrast, there was less *performance* variability in a later period than in an early period consistent with traditional models of learning-driven convergence. The contrast between results for the innovation feature and for performance reveals that the same learning context can produce divergence in one learning outcome and convergence in another. We speculate that this pattern is consistent with the impact of two specific forms of organizational learning—direct experience using organizational experimentation and deliberate, selective vicarious learning.

This paper makes three important contributions to the organizational learning literature. First, it explicates and tests theory about whether the accumulation of industry-level implementation experience with a major administrative innovation can increase, instead of reduce, industry-level variability in learning outcomes. Second, it advances contingency theory concerning specific processes that determine whether convergence or divergence will dominate industry–level learning outcomes. Third, it advances population-level learning by proposing a simpler approach to defining population-level learning, while also illuminating factors that affect the distribution of practices in an organizational population.

Theory and hypotheses

Systematic studies have started to unravel how different organization-level and population-level learning activities change industry-level outcomes such as production efficiency (Argote, 1999) or the rate of abandonment of new practices (Terlaak and Gong, 2008). This paper, in contrast, tackles the question of variability of industry-level learning outcomes. *Learning-based convergence* models represent a special sub-set of convergence approaches to systematic change. They focus on how learning processes drive convergence in contrast to non-learning factors such as concerns over legitimacy (Tolbert and Zucker, 1983; Scott, 2008) normative expectations (DiMaggio and Powell, 1983) or competitive selection (Aldrich and Ruef, 2006). Within organizations, theory has long emphasized that learning during the implementation of manufacturing innovations and related production process improvement should yield both better performance and less variability in outcomes (Flynn, Sakakibara, and Schroeder, 1995; Benner and Tushman, 2003). Research on industry-level learning and experience curves has found increasing mean performance levels, learning at decreasing rates, and varying learning rates across industries (Lieberman, 1984; Argote and Epple, 1990). Empirical work on industry-level learning effects has not yet offered a coherent body of work on industry-level variability in learning outcomes, however, leaving an important gap which this paper seeks to fill.

Following established learning research, we define organizational learning as occurring when experience systematically modifies an organization's knowledge base or behavior (Argote, 1999; Madsen and Desai, 2010). It may or may not produce useful results for the learning agent or others (Levinthal and March, 1993). Although most theories focus on mean levels of outcomes rather than outcome variability, the idea of reduction of variability does appear in some models of individual learning (Mazur and Hastie, 1978), organizational learning (Argote and Epple, 1990; Tyre and Orlikowski, 1994), and population-level learning (Miner and Anderson, 1999; Aldrich and Ruef, 2006). A variability reducing learning process inside an organization occurs when experience with a new manufacturing process decreases the variability in unit quality produced, but at the same time increases the mean quality level. Christensen et al. (2007) found decreased variance in lead times in supply chains increased financial performance, for example. Intuitively, if all organizations in a population learn the one best way to implement an innovation, this should produce convergence in features and performance as they all approach the limit of the value of the innovation (Miner and Anderson, 1999).

This paper theorizes instead that industry-level variability will be generated by three mundane ongoing organizational learning processes: vicarious learning by multiple organizations, deliberate learning from the organizations' own experience, and ongoing organizational learning in the presence of population-level learning. Vicarious learning occurs when an organization draws on the experience of other organizations rather than on its own experience (Haunschild and Miner, 1997; Kraatz, 1998; Baum, Li, and Usher, 2000; Terlaak and Gong, 2008). Deliberate learning from the organizations' own experience includes both trial-and-error learning (Miner, Bassoff, and Moorman, 2001; Rerup and Feldman, 2011) and learning from performance feedback and aspiration levels (Cyert and March, 1963; Greve, 1998, 2003). We define population-level learning as changes in industry-level norms and rules that arise from shared experience (Miner and Haunschild, 1995; Kraatz, 1998; King and Lenox, 2000).

In developing our causal arguments we call on prior work that has flagged four factors that should shape which pattern dominates (Miner, Haunschild, and Schwab, 2003) but has not advanced a coherent approach. First, during vicarious learning, organizations can use multiple targets, switch the between different learning strategies and make errors in learning from others (Miner and Raghavan, 1999). Second, there can be strong interdependencies between the impact of different innovation features, or epistasis, which will lead to changes producing dramatically different outcomes (Becker and Gerhart, 1996; Levinthal, 1997). Third, organizations can pursue novelty in action for own sake, in pursuit of experimental learning or because only extreme outcomes are rewarded (March, 1991). Finally, the interaction of population-level learning of new collective rules and norms and organizational learning can generate variable outcomes (Haunschild and Sullivan, 2002). These general ideas have not been developed in detail nor specifically linked to the three fundamental organizational learning processes highlighted in this paper. After describing our research context, we first hypothesize about how the three main learning processes influence the variability in a key administrative innovation feature, and then develop their impact on industry-level performance variability.

Research Setting

We investigate our hypotheses in the context of a well-documented major administrative innovation in the U.S. Major League Baseball (MLB) industry that "…brought about the greatest single change of this century in the business structure of the game [of baseball]" (Smith, 2000: 200). Beginning in the early 1920s, the St. Louis Cardinals innovated a hierarchical system of affiliated minor league teams to create a vertically-structured internal labor market along with related scouting, training tracking and management systems (Anderson, 1975; Golenbock, 2001). The administrative innovation became known as a "farm-system." Instead of acquiring major league-ready players from independent minor league teams, the Cardinals signed long-term contracts with a large number of promising players at early stages of their careers and then systematically moved these players through an ordered set of affiliated teams. The distinct characteristic of the system was the hierarchical arrangement of affiliated teams, with a key feature being the number of affiliated teams.

Administrative innovations are more ambiguous, open to more interpretations, and often can be implemented through a variety of combinations of different routines than technological innovations (Westphal, Gulati, and Shortell, 1997). These elements characterize the farm-system which required MLB clubs to develop a set of novel capabilities to establish and manage relationships with their ordered set of affiliated minor league teams and to recruit, train, select and promote a substantially larger and more heterogeneous pool of potential major league players (Anderson, 1975). Our theoretical focus is on the difference of industry-level variability between an early and late period after the first implementation of the farm-system innovation. Specifically, we examine how low and high industry-level experience influenced industry-level-variance in two important learning outcomes: the number of teams in a MLB club's farm-system and the performance advantage when one club had implemented the farm-system and the other had not.

The number and identity of MLB clubs remains stable during our study period, and all clubs eventually adopted the system. There were also no major exogenous technological or societal shocks during the study period, making this a good context to investigate learning processes. These characteristics also let us rule out important potential contingencies such as abandonment of the innovation itself (Terlaak and Gong, 2008), entrance and exit of competitors (Hopenhayn, 1992), varied starting conditions (Levinthal, 1997; Anderson, 1999), and exogenous events including major technological discontinuities (Tushman and Anderson, 1986). We include descriptive data of the focal micro-processes in our research setting. These were not used to develop theory but help illustrate the relevance of specific learning processes to our research setting.

Divergence in Administrative Innovation Features

We first focus on the degree to which industry-level variability in an innovation feature changes with the accumulation of implementation experience from an early period to a late period after the first implementation of an innovation. To examine this issue we track a core innovation feature, the number of minor league teams in a MLB club's farm-system, which we call farm-system size. Farm-system size represents a core feature of the administrative innovation because it not only directly affected the breadth and depth of the internal labor market, but also increased the complexity and diversity of a club's internal network relationships, creating both new opportunities and new coordination and contracting challenges (Anderson, 1975). Thus, it is not surprising farm-system size received substantial attention from clubs that implemented the farm-system innovation and from the MLB industry as a whole.

Learning about implementation of an administrative innovation focuses attention on questions such as what does it mean to implement this innovation, what are its key features and how does one execute them (Ansari, Fiss, and Zajac, 2010; Fiss, Kennedy, and Davis, 2011). It's intuitively appealing that as an industry accumulates more implementation experience with an innovation, the innovation features organizations implement should become more similar. First, when organizations look at the aggregate actions of others, they often assume the most frequently deployed innovation features have higher value (Abrahamson and Rosenkopf, 1993; Haunschild and Miner, 1997) or offer greater legitimacy (DiMaggio and Powell, 1983). On the surface, this should promote convergence. Second, when organizations learn from direct experience by intentionally or accidentally experimenting with different implementation approaches they should eventually discover the most effective features and thus converge (Benner and Tushman, 2002). Third, when organizations are learning at the same time the industry as a whole learns, emerging industry norms should promote and perhaps accelerate increasing similarity (Abrahamson, 1991; Abrahamson and Fairchild, 1999).

In this study we propose such convergence in administrative innovation features will not necessarily occur. Instead we argue industry-level variability can be generated by vicarious learning, learning from direct experience, and organizational learning in the presence of population-level learning.

Vicarious learning. Vicarious learning occurs when the learning unit draws on the experience of others rather than on direct experience (Huber, 1991). Multiple studies have confirmed that organizations orient their behavior on their observation of similar activities at other organizations and draw inferences from observing others (Fligstein, 1985; Haunschild and Miner, 1997; Greve, 1998; Kraatz, 1998; Baum, Li, and Usher, 2000). In one-to-one vicarious learning, a focal organization draws on the experience of other individual organizations as a basis for its own learning. In a second form of vicarious learning—learning from collective patterns—organizations draw on industry-level patterns as the industry-level experience accumulates to inform their own learning. The learning is at the organizational level, but the pattern of action informing it is at the industry-level. Both types of vicarious learning can produce variability in what is implemented.

First, as organizations try to observe, copy or understand the activities of other individual organizations they can take away very different interpretations of what a given observed organization was doing (Burns and Wholey, 1993; Westphal, Gulati, and Shortell, 1997). An organization's own behavior may not match what was actually done. Drawing on industry-level collective patterns can produce diversity across firms even if all correctly observe what is being done if each organization's attention is directed at different indicators (Haunschild and Miner, 1997). Some organizations use the industry statistic of most frequent form while others may imitate what is done by larger or similar organizations (Terlaak and Gong, 2008). Organizations sometimes choose multiple targets to learn from or switch between different imitation modes over time (Miner and Raghavan, 1999). If some clearly superior implementation approaches exist, organizations might be expected to eventually correct towards the better form. However, considerable evidence reveals many barriers to such effective observation, whether from bias in the observing firms, sampling challenges, or barriers to having complete data (Denrell, 2003).

Industry transparency in MLB encouraged clubs to try to learn vicariously from one another (Burk, 2001). Historical accounts suggest both one-to-one vicarious learning and organizational learning from collective patterns occurred in our research setting. After observing how the Cardinals used their Rochester farm team, the New York Yankees decided to duplicate the farm-system innovation (Sullivan, 1990: 108). Historical descriptions of club behavior also showed considerable awareness of industry-level patterns, shared and known through annual meetings of club management or open statistics on such innovation features as farm-system size (Tygiel, 2000; Burk, 2001)—consistent with learning from collective experience. Systematic quantitative evidence also indicates that clubs tended to adjust their farm-system size towards the industry average when they had recently experienced a performance decline (Schwab, 2007)—consistent with the importance of industry-level patterns as a learning source.

Learning from direct experience. In simple behavioral trial-and-error learning organizations repeat what appears to work or avoid what seems to produce detrimental effects—perhaps with little deliberate attention to the process (Burgelman, 1994). In other models, organizations repeat current actions until outcomes fail to meet aspiration levels at which point organizations begin to search for new action options (Cyert and March, 1963; Greve, 1998). In either event, variability in outcomes of local action can create organizational action trajectories that vary over time (Yelle, 1979). A set of organizations implementing the same innovation can reach quite different understandings and therefore undertake varied behavior (Argote and Epple, 1990). Substantial research highlights the difficulty in making consistent and accurate inferences even when clear performance data are available (Levinthal and March, 1993). Kim and Miner (2009) showed for example that even the impact of extreme success or failure was not linear and depended on prior levels of the same type of experience.

Deliberate experimentation represents a special form of performance feedback learning (Anderson, 1999; Greve and Taylor, 2000) in which organizations deliberately change innovation features with the intention of learning after observing outcomes (Argote, 1999; Miner, Bassoff, and Moorman, 2001). Tyre and Orlikowsky (1994) report that much of this experimentation occurs in the period directly following the early implementation steps but that some experimentation can occur during later stages. Rapidly advancing competitors can also prompt continuing experimentation (Greve and Taylor, 2000). If some organizations experiment with new ways to implement an innovation but others retain earlier approaches, this will increase the level of industry-level variability.

Organizations also sometimes attend to different outcomes of their own experience. Lounsbury (2007) showed how mutual fund decisions to contract with independent professional money management firms depended on both the type of mutual fund, nongrowth and growth, and the salience of the specific outcome indicator, relative fund expense ratio and fund performance. Additionally, organizations sometimes alternate the degree of attention they give to internal experience. For example, they may attend to internal experience if they are above aspirations but look outside their own experience after a failure experience (Cyert and March, 1963).

Historical MLB studies illustrate club efforts to learn from their own experience about how to implement the farm-system. Clubs had high levels of information about their own activities and their own performance at both absolute levels and in contrast to others, in part due to the extensive dissemination of statistics on players and clubs (Dewey and Acocella, 2005). Industry publications reported the farm-system affected performance (Sporting News, 1931), which encouraged clubs to look for specific connections even though it may have been hard to know how best to implement it. The Yankees tried integrating a farm-system with the club's successful traditional system for acquiring major league-ready players (Burk, 2001: 51), and the Cardinals invented tryout camps to select players for their farm-system and continued to experiment in how to best exploit this innovation feature (Burk, 2001; Golenbock, 2001).

Organization learning in the presence of population-level learning. After early implementation efforts, an industry as a whole often develops routines and practices based on its collective experience and shared understandings of the innovation (Rosenkopf and Tushman, 1998). In such population-level learning, industries often develop new rules about how members should implement an innovation, either as an industry attempts to reduce its riskiness or to enhance its value (Westphal, Gulati, and Shortell, 1997). For example, collective analyses of airline accidents (industry experience) often led to changes in FAA regulations (industry norms: Haunschild and Sullivan, 2002).

Industry-level variability in administrative innovation features can arise when individual organizations repeatedly try to learn while the industry itself is learning. First, some organizations will proactively anticipate changes before new rules or regulations are introduced, while other organizations will react to changes (Brown and Eisenhardt, 1997)—producing variability. Second, higher-level rules when implemented under different conditions will often increase variably in execution activities (Zeitlin and Herrigel, 2000; Miner et al., 2010). In the airline context, differences in fleet structure, state of equipment and corporate capabilities often led to differences of how individual airlines implemented recommended and required changes (Donoghue, 1998).

Historical accounts emphasize how the MLB commissioner initially strongly discouraged the implementation of farm-systems, but faced increasingly effective pressure from club owners to legitimize the practice (Burk, 2001). Conventions and lower level rules about permissible practices developed based on shared experience, such as in 1931 when MLB clubs agreed "a big league franchise could assign players down without counting them against its forty-man reserve limits, then reclaim them later" thus avoiding the requirement of paying a $400 fee to a minor league team every time the MLB club recalled players back to the majors (Burk, 2001: 46-47). Although no formal industry-level norm directly regulated farm-system size, collective population learning over time changed the broader institutional framework for its implementation in which each club attempted to learn from its own or others' experience.

The collective influence of vicarious learning, learning from direct experience, and organizational learning in the presence of population-level learning suggests the following:

Hypothesis 1: Industry-level variability in an administrative innovation feature will be lower in the early period where there is less industry implementation experience accumulated and higher in the later periods with greater accumulation of industry implementation experience.

Divergence in Organizational Performance Advantage

Our second focus is industry-level variability in the performance advantage when one club had implemented the farm-system and the other had not. To examine this issue we track MLB clubs' winning games, an unambiguous metric that measures performance consistently over time. As mentioned earlier, commentary by industry experts reported clear connections between deploying the farm-system and winning baseball games (Sporting News, 1931). On average, farm-systems increased clubs' winning percentages by 0.07 points relative to non-implementers of the farm-system (Olson and Schwab, 2000: 553).

Feature-focused learning about implementation focuses organizations on what features are available and how to implement them. Performance-focused learning focuses organizations on how to use features to improve outcomes (Greve, 2003). Organizational learning theory often implies reduced organizational performance variability as an industry accumulates more implementation experience. First, as organizations learn vicariously from other organizations, they tend to replicate innovation features that seem to improve performance, and move closer to each other in terms of performance (Greve, 1999; Baum and Dahlin, 2007; Kim and Miner, 2007). Second, when learning from direct experience, firms can selectively retain practices that reliably improve performance. This ongoing learning can reduce industry-level performance variability as the organizations all hone in more effective implementation approaches and move closer to the performance limit of the innovation (McKee, 1992). Finally, as they learn, organizations will adapt to the same emerging industry-level norms, rules and infrastructures designed to improve performance and leading all organizations closer toward the performance limit of the innovation. Consistent with this idea, for example, much work on the importance of intellectual property assumes that in the absence of explicit barriers to others deploying an innovation, it will not be possible to maintain performance differences (Teece, 1988).

In our study, we propose that such industry-level performance convergence will not necessarily occur. The same three generic learning processes that affect divergence in features should also affect divergence in performance, with some factors playing a stronger role for this learning outcome.

Vicarious learning. Performance-focused vicarious learning suffers from major challenges associated with accurate observation and understanding how an administrative innovation truly worked for others (Levinthal and March, 1993). Two factors play especially important roles in potentially increasing organizational performance variability from repeated vicarious learning.

First, for some innovations the main performance-related features operate more or less independently. In those events, organizations can 'hill climb' towards increased performance by adding useful features observed in others in whatever combination and sequence they prefer (Levinthal, 1997). However, in other cases the impact of specific features depends on the presence of other innovation features or organizational contexts for their value. In those cases, if organizations follow an implementation approach that unequivocally worked for another organization, it can fail to improve and even harm their performance (Levinthal, 1997; Axelrod and Cohen, 2001). Vicarious learning in the presence of high interdependence or epistasis between features, then, can promote industry-level performance variability.

A second crucial way vicarious learning can produce performance divergence arises when organizations use multiple vicarious learning targets or switch between different learning strategies (Haunschild and Miner, 1997). Organizations use varied proxies as indicators that an innovation feature is not only popular but effective. They can look to organizations similar in size for some features (Haveman, 1993) or to those where they can see good outcomes in geographically close organizations (Lee and Pennings, 2002). Combining or switching between different imitation targets can produce mutually contradictory innovation features that produce unexpected and varying performance outcomes (Miner, Haunschild, and Schwab, 2003). In this case, ongoing repeated vicarious learning will generate improvements in the performance of some organizations while others experience a deterioration of their performance, thus increasing industry-level variability.

As mentioned earlier, transparency within MLB enabled clubs to learn from one another (Burk, 2001). However, it is not clear if clubs were able to replicate the observed success with the farm-system of other clubs. For example, the Yankees duplicated the farm-system innovation by establishing an affiliation with the Newark Bears after observing the Cardinals minor league affiliate in Rochester, NY (Sullivan, 1990: 108). The Yankees, however, did not implement other features of the Cardinals farm-system, such as scouting practices (Burk, 2001: 51). If farm-system scouting practices and the size of farm-systems are interdependent, then the performance advantage of the Yankees and Cardinals might not converge. Moreover, prior research has indicated that the clubs adjusted farm-system size by moving towards the industry average, but only when their performance had stagnated or declined in the past year (Schwab, 2007) confirming the feasibility of shifting templates for vicarious learning from different sources.

Learning from direct experience. If a MLB club deliberately experiments with innovation features, such as farm-system size, and these features have a systematic impact on performance, then performance should vary along with feature changes. In addition, interpreting the impact of its own individual administrative innovation features—such as the scouting system, training systems, farm-system size, use of statistical analysis or approaches to player assignment—can seriously challenge the implementing organization (Levinthal and March, 1993). Finally, as described above, the impact of a given innovation feature can depend on combining it with other features. In these cases, learning from direct experience will not only fail to lead organizations to the same implementation approaches, as predicted in our first hypothesis, but will also produce varied performance outcomes. The more different features are interdependent, the greater the possibility that variation will increase rather than decrease over time. Small differences in combinations of features can produce large differences in performance outcomes. This can be enhanced further if negative outcomes stimulate even more experiments (Greve, 1998).

Anecdotal evidence from MLB suggests clubs learned from their direct experiences and experiments aimed directly at improving performance through their farm-systems. For example, the Cardinals were the first club to implement pitching machines to develop their minor league hitters and a "contraption of strings" to teach minor league pitchers control (Vecsey, 2008). The Chicago Cubs "brought in a battery of statisticians to break down every conceivable game situation involving pitchers and hitters" to enhance their farm-system (Dewey and Acocella, 2005: 259). The Yankees implemented the farm-system administrative innovation with their existing practice of purchasing contracts of major league ready talent, like Joe DiMaggio, from independent minor league teams (Burk, 2001; Vecsey, 2008). Prior research has also offered quantitative empirical evidence of MLB clubs learning from their own experience in the absence of prior performance decline (Schwab, 2007).

Organization learning in the presence of population-level learning. Population-level learning often creates norms and routines for best practices (Kraatz, 1998; King and Lenox, 2000). These norms, however, do not affect organizations uniformly—constraining or enabling some organizations more than others (DiMaggio and Powell, 1983). This can produce variability in performance outcomes (Haunschild and Sullivan, 2002). In addition, differences in the timing of learning can generate variability. Organizations learning earlier will have potentially less or different guidance from population-level learning than those organizations learning after the industry has accumulated more implementation experience. Consequently, guidance taken from population-level learning can have performance implications that can increase variability in later periods.

Initial MLB rules against "working agreements" created risks for the clubs that nevertheless continued to use them, and favored well-endowed organizations that could afford outright ownership of minor league teams (Burk, 2001). The later legalizing of working agreements in 1931 changed the competitive landscape and the ways in which clubs learned how to implement their farm-systems. In addition, the MLB commissioner, at times, selectively and unpredictably enforced norms and required targeted organizations to release farm players, which directly affected their subsequent performance (Burk, 2001; Vecsey, 2008). As clubs tried to learn from their own experience or watching others, their learning context would thus differ over time, with potentially different performance implications for the same behavior or practice.

The collective influence of vicarious learning, learning from direct experience, and organizational learning in the presence of population-level learning suggests the following:

Hypothesis 2: Industry-level variability in organizational performance advantage of the administrative innovation will be lower in the early period where there is less industry implementation experience accumulated and higher in the later periods with greater accumulation of industry implementation experience.

DATA AND METHODS

We collected MLB data from 1920-1941 to test our theory. Sources used to collect data—the *Minor League Digest* (1936-1940), detailed lists generated by Jerry Jackson, a member of the Society of Baseball Research, and the *Baseball Bluebook* (1919-1940)—were the same as those used for earlier work (e.g. Schwab, Olson, and Miner, 2002; Schwab, 2007). However, the data are used for very different purposes. Our interest is in industry-level learning outcome variability as the industry accumulates implementation experience while earlier work focused on the impact of the farm-system on individual MLB clubs (Olson and Schwab, 2000) and on how organizational-level learning influences features of administrative innovation at the individual organization-level (Schwab, 2007).

Scholars have long noted that sport industry data can offer unique internal and external validity advantages (e.g. Allen, Panian, and Lotz, 1979; Wolfe et al., 2005). Thus, MLB data continue to be used frequently to examine important fundamental theoretical questions (e.g. Barden and Mitchell, 2007; Sirmon, Gove, and Hitt, 2008; Graffin and Ward, 2010; Cotton, Shen, and Livne-Tarandach, 2011). One particular advantage was the general stability of the MLB setting. For example, we are able to confidently rule out the threats related to changes of the set of organizations in the industry because MLB did not add or drop any clubs during the study period.

The core construct of the farm-system lay in the existence of a hierarchical set of teams affiliated with a MLB club, through which players could be moved and developed (Anderson, 1975). Following prior research on the farm-system in MLB (e.g. Olson and Schwab, 2000; Schwab, 2007), we operationalize the implementation of the farm-system by a MLB club as follows. We coded a club as possessing a farm-system if it had: (1) at least two low-level minor league teams (e.g., B, C, D, or unspecified) playing at different competitive levels (e.g., both teams were not playing in B leagues); and (2) at least one minor league team playing at a high level of competitiveness (e.g., AAA, A, or A-1). As Figure 1 demonstrates, when MLB clubs implemented the farm-system, they did not all start with the same number of farm teams and as time passed, every club expanded and reduced the number of teams in their farm-system. Moreover, only 143 of the 310 minor league teams in 1939 were affiliated to a MLB club. The remaining large number of independent minor league teams and their increasing interest in joining a farm-system (Burk, 2001) suggest no substantial constraints for late movers to build or expand their farm-system.

Our comprehensive panel data set covers the population of 16 MLB clubs for each season from 1923 to 1940. We do not include data beyond 1940 to minimize the disruptive effects of World War II when over 500 MLB players and over 5,000 minor league baseball players served in the U.S. military (Vecsey, 2008). For our analyses, we created two equal periods of seven years in length. We define an early and late period of accumulated innovation implementation experience as 1927-1933 and 1934-1940 respectively. We also ran analyses on a three period split—early (1926-1930), middle (1931-1935), and late (1936-1940)—which produced consistent results. This approach to measuring period of innovation implementation is consistent with previous administrative innovation implementation studies (e.g. Westphal, Gulati, and Shortell, 1997; Kennedy and Fiss, 2009). Our approach accounts for implementation experience, accumulating simultaneously on the organization and the population-levels, and avoids endogeneity problems for any attempts to separate their respective effects on industry-level learning outcome variability.

Because of the importance of learning context for the effects of organizational learning (Lave and Wenger, 1991; March, 1999), we reviewed contemporaneous industry publications including *The New York Times* (1927-1940), *Sporting News* (1931) , *Baseball Bluebook* (1919-1940), *Minor League Digest* (1936-1940), *Total Baseball* (Thom and Palmer, 1989), and industry and team histories (Anderson, 1975; Burk, 2001; Dewey and Acocella, 2005; Vecsey, 2008). We used the extensive qualitative data to help in our choice of proxy variables, to understand industry conditions and to probe the general feasibility of theoretically anticipated processes, but we did not use these data for theory building.

Assessment Strategy

The evaluation of variability requires comparisons between groups of observations. Thus we compare the standard deviation of the two key learning outcomes, farm-system size and MLB club performance, between early and late periods. The small number of clubs competing each year and the gradual change in industry-level implementation experience between subsequent years does not permit us to use variance for each year as an unit of analysis, leading to our early and later period approach. Although there are multiple approaches to defining variability (Miner, Haunschild, and Schwab, 2003), we use variance for this study because both our outcome variables are continuous variables on a single dimension.

Simple split-group comparison. In a first approach, we perform simple split-group comparisons of variance differences in our two industry-level learning outcome dependent variables: farm-system size and MLB club performance advantage. For this simple and straightforward evaluation of our hypotheses, we evaluate the contrast in learning outcome variability by comparing between earlier and later periods with lower and higher industry-level implementation experience. The distribution of both dependent variables showed reasonable normal distribution tendencies. Therefore, we use a robust F-test of standard deviation differences based on 10% trimmed means that accounts for unequal subsample size and moderate deviations from normality (Brown and Forsythe, 1974). We also examined the coefficient of variation, which captured the size of the standard deviation relative to the mean.

Multi-level mixed effect models. Split-group comparisons do not control for remaining differences between organizations. Thus, we also use multi-level mixed effect models for a more sophisticated test of variability. These models allow us to control for relevant fixed differences in resource availability between clubs and fixed league effects. We then estimate the fixed and random effects of having a farm-system during earlier and later time periods to test for changes in learning outcome variability (McCulloch, Searle, and Neuhaus, 2008).

To assess whether there is a difference in variability in the later period versus the earlier period, we first develop a model for the dependent variable in which the standard deviation for the early period and the later period are constrained to be the same. We then compare that model to one in which they are unconstrained. If the unconstrained model improves model fit and shows a larger standard deviation for the later period than the earlier period then evidence exists for higher variation in the later period for the relevant dependent variable.

Dependent Variables

Industry-level variability in farm-system size. To measure industry-level variability in farm-system size we first count the number of minor league teams affiliated to a MLB club for each year a club met the condition for farm-system implementation. Then we accounted for the four-years that it took clubs to establish their farm-system and graduate major-league ready players. For example, the Cardinals started their farm-system efforts in 1923 and had established their farm-system in 1927 which provided us fourteen separate club-year farm-system size observations and the Yankees had established their farm-system in 1930 which provided us ten club-year farm-system size observations. In total there are 106 club-year farm-system size observations. As described above, we then calculate the standard deviation of farm-system size for the early and later period.

Industry-level variability in MLB club performance advantage. In many settings, only overall organizational performance information that aggregates the result of simultaneous competition with multiple competitors is available. Such aggregated performance information creates substantial interpretation and modeling challenges, including those related to controlling for innovation diffusion effects (Barnett and Carroll, 1995). Our data set contains regular season win/loss records for all 56 matched pairs of regular season games between clubs in their respective leagues—during the time period we study, MLB did not schedule regular season interleague play. The balanced competition in the MLB industry implies that one team's win is another team's loss and the average seasonal win/loss ratio across all teams is always 0.5. In our matched pair dataset, however, performance advantage effects are estimated based on win/loss advantage of clubs that have already established a farm-system, looking at all the games they played against clubs that had no such system. Importantly, this approach controls for effects related to clubs more frequently competing against clubs with farm-systems as this administrative innovation diffused. If all clubs implementing the system had an equal advantage over non-implementers, there would be no variance in the performance advantage.

We measure specific MLB club performance advantage by calculating the fraction of games this club won over a specific competing club for each matched pair in each of the seasons. Prior research has demonstrated that advantages associated with a club deploying a farm-system took four or more years of implementation experience with the farm-system to materialize (Olson and Schwab, 2000) due to the time needed to train and graduate players (Anderson, 1975). We account for this four-year performance lag in our farm-system measure. Our results, however, are robust for alternative lag specifications.

Independent Variable

Accumulated industry-level implementation experience. Our causal theory focuses on total accumulated implementation experience in the industry, which we operationalize by contrasting an early period, when accumulated industry-level implementation experience was low, with a later period, when the accumulated industry-level implementation experience was substantial.

Control variables

In our mixed model analyses we account for time-variant resource differences using changes in the size of a club's *local market* based on U.S. Census estimates of city population. Dummy variables control for divided fan loyalties when a city had *two clubs in the same city* and *three clubs in the same city*. Our *league* variable captures if clubs belonged to either MLB’s National League, coded 1, or MLB’s American League, coded 0. When testing our second hypothesis, we also controlled for one-year lagged performance effects of the *reserve team* (Anderson, 1975; Olson and Schwab, 2000), a prevalent practice in which major league clubs used a single high-level minor league team to provide substitute players for short-term needs.

RESULTS

Variability in Farm-system Size

Table 1 reports the descriptive statistics for our study variables. Figure 2 presents a visual representation of farm-system size and variance over our study period. It suggests industry-level variability in farm-system size remained high and appeared to increase as MLB accumulated more implementation experience with the farm-system administrative innovation. MLB clubs regularly adjusted the size of their farm-system, at times adding more teams and other times dropping teams (see Figure 1). This suggests the variability during later time periods came from ongoing moderate increases and decreases in the size of existing farm-systems and not just from a simple change in the mix of new and old implementers.

Split-group comparison. Table 2 shows the results of simple split-group analyses comparing the variability of farm-system size between early and late periods. A robust F-test for standard deviation differences of farm-system size shows an increase in variance as the industry-level implementation experience accumulated (ΔS.D. = 4.13; F = 4.91; $p < .05$). This robust F-test compensates for sample size differences and moderate deviations from normality (Brown and Forsythe, 1974). In addition, the coefficient of variation, which measures the size of the standard deviation relative to the mean, increased in the later period, indicating that the increased standard deviation was not simply the result of higher means.

Multi-level mixed effect model. Model 1 in Table 3 forces the random effect estimates for the late period and the early period to be identical (Log Likelihood = -297.78). Model 2 allows the random effect estimates to be independent, improving the model fit (Δ Log Likelihood = 1.12; $\chi^2 = 2.24$; $p = 0.07$). The random effect estimate for the late period (S.D. = 4.82; $CI_{95\%}$: 3.09 to 7.52) is substantially larger than the random effect for the early period (S.D. = .02) which supports the hypothesis that there was more variability in the late period than in the early period.

Variability in MLB Club Performance Advantage

We define MLB club performance advantage as the win/loss advantage of clubs that have already implemented the farm-system, looking at all the games they played against clubs that had no such system. We created two dummy variables to identify observations when one of the competing clubs had a farm-system and the other did not: one dummy for the early period and the other dummy for the late period. Table 4 reports the descriptive statistics for variables in the head-to-head data set used for our tests of the effect of accumulation of innovation implementation experience on industry-level variability of farm-system related performance advantage experienced by different MLB clubs. Figure 3 provides a visual representation of

MLB club performance advantage means and variances over time. It suggests industry-level variability in performance advantage decreased as industry-level implementation experience increased over time.

Split-group comparison. Table 5 shows results of split-group analyses comparing the variability in MLB club performance advantage between the early and late period. A robust F-test for standard deviation differences shows a decrease in variance as the industry accumulated more implementation experience (Δ S.D. = .04; F = 6.78; p < .01). The coefficient of variation also decreased, indicating that variability decreased proportionally.

Multi-level mixed effect model. Model 1 in Table 6 forces the random effects estimates for MLB club performance advantage in the early period and the late period to be identical (Log Likelihood = 603.23). Model 2 allows the random effect estimates to be independent which improves model fit (Δ Log Likelihood = 1.44; $\chi 2$ = 2.89; p = 0.09). However, the random effect estimate for the late period (SD = 0.03) is smaller than the random effect for the early period (SD = 0.08; CI $_{99\%}$: .04 to .20). This pattern suggests that there was substantially less variability in the later period than in the earlier period, which is inconsistent with our second hypothesis.

Robustness of Findings

Variability in farm-system size. Industry accumulation of implementation experience in the late period is a composite of the experience of early implementers with high levels of direct implementation experience and the increasing number of new implementers with limited direct implementation experience but who can also draw on the accumulated industry-level experience. We restricted our sample to data for the first four years or less of organizational-level implementation experience for all clubs with an established farm-system. Results of restricting the sample to these recent implementers (last two columns of Table 2) show that for the late period, the standard deviation of farm-system size was three times larger (Δ S.D. = 2.00; F = 5.83; p < .05) and coefficients of variation doubled. When we restricted our multi-level mixed effect model to only recent implementers (Model 5 in Table 3), the random effect for the late period is smaller, but still larger than the random effect for the early period. These results suggest that the later period increased variability is not the result of early implementers growing with time and being contrasted with newcomers who have started small.

Close inspection of Figure 1 might raise concerns that the increase in farm-system size variability after 1934 was caused by a single club, the St. Louis Cardinals, who aggressively increased the size of their farm-system. We ran our analyses excluding the Cardinals. The split-group comparison results show that industry-level variability in farm-system size increased (Δ S.D. = 2.61; F = 7.86; p < .01). The corresponding multi-level mixed effect model confirmed these results. Thus, our hypotheses were also supported in models that excluded the first-mover that created the largest farm-system during the 1930s. We also used maximum likelihood estimation (Table 5, Model 3) and controlled for autocorrelation (Table 5, Model 4) and the results were similar.

Variability in MLB club performance advantage. We also restricted our split-group comparisons to recent implementers (see the last two columns of Table 5) to remove early versus late implementer effects. The robust F-test for S.D. differences indicates a significantly lower performance variance for the late period (Δ S.D. = .05; F = 1.85; p < .05). The coefficient of variation also decreased, consistent with our initial analyses. When we restricted our mixed-effect analyses to only recent implementers (Table 6, Model 9), the observed variability reduction is even stronger (Δ S.D. = .09; n.s.).

To test whether our results were dependent on the first-mover, we also ran our split-group analyses excluding the Cardinals. We no longer observed a statistically significant decrease in

S.D. (Δ S.D. = .02; F = 1.70; n.s.). Corresponding mixed effect models were consistent with this outcome. One interpretation of this pattern is that excluding the first mover, the clubs showed a pattern of sustained variability in performance, rather than a pattern of convergence.

Finally, we also checked for robustness of our mixed-effect analyses using maximum likelihood estimation (Table 6, Model 3), models without autocorrelation corrections (Table 6, Models 4, 5, 7 and 8), models constrained to later years (Table 6, Models 5 and 8) and models with log-transformed dependent variable (Table 6, Models 6, 7, 8, and 10). We also considered whether our variability results might be due to differences in sample sizes for the different time periods. However, the robust F-test we used compensates for sample size differences (Brown and Forsythe, 1974) and other alternative measures of S.D. differences led to similar results (Levene, 1960; Brown and Forsythe, 1974). Taken together the results from these various additional analyses confirmed the results from our initial analyses.

DISCUSSION

Results support our fundamental argument that the accumulation of industry experience with an administrative innovation can increase the variability of innovation features under certain conditions. In contrast, however, accumulation of industry experience led to convergence in performance. This pattern of one divergent and one convergent learning outcome represents an unexpected finding that deserves attention in its own right. In this section, we discuss the implications of these findings for theories of organizational learning.

Variability in Administrative Innovation Features

Our analyses clearly support our first hypothesis that the variability in innovation features can increase as the industry accumulates innovation implementation experience. The higher late-period variability in farm-system size occurred even in the face of evidence from research at a different level of analysis that larger farm-system size is associated with higher MLB club performance (Schwab, Olson, and Miner, 2002) and that clubs tended to adjust their farm-system size towards the industry mean when their recent prior performance had stagnated or deteriorated (Schwab, 2007). If clubs were all simply learning best practices efficiently from performance feedback or vicarious observation, one would expect convergence of farm-system size over time. Our results indicate this did not occur during our study period.

Our theory explicated variance-inducing mechanisms that can occur within basic organizational learning processes of vicarious learning from others, direct learning from one's own experience, and learning while the population learns as well. Data availability prevented us from investigating directly the relative impact of these proposed underlying learning processes in our quantitative models. Historical reports, however, support the relevance of these learning mechanisms in our empirical context. During the same period of time, other potential variance-inducing mechanisms, such as extremely varied starting conditions (Levinthal, 1997; Anderson, 1999), external shocks (Tushman and Anderson, 1986) or abandonment of the innovation (Terlaak and Gong, 2008) did not appear to occur in our empirical setting, reducing the chances they generated the observed results. The qualitative accounts of how actual innovation features developed and occurred within MLB is consistent with our theory about how three mundane learning processes unfold and can produce divergence rather than convergence. Together our quantitative and qualitative findings provides support for the feasibility of learning based divergence patterns and guidance for future empirical work to probe in more detail these underlying processes and their boundary conditions.

Such future research is also encouraged based on the important potential implications of our variability findings for industry-level adaptation processes (Nelson and Winter, 1982; Miner and Anderson, 1999; Aldrich and Ruef, 2006). Low levels of variation can make an industry dangerously fragile (Levinthal and March, 1993). An industry with more variants of the innovation can potentially better survive exogenous shocks if a new setting erases the value of the dominant form (Suchman, 1995; Anderson, 1999; Aldrich and Ruef, 2006). In addition, variability in an innovation feature can provide broader samples of action and outcomes that support continuing vicarious learning (Haunschild and Beckman, 1998; Kim and Miner, 2007).

In other cases, however, industry-level variability can have mixed implications. High levels of variability have been associated with negative adaptability outcomes. Variability in an innovation feature can prevent an industry from achieving useful standardization of the innovation (Tushman and Anderson, 1986; Greve and Rao, 2006). Moreover, external investors sometimes interpret instability and heterogeneity of innovation features as indicators of risk and, at other times, as indicators of opportunity (Aldrich and Ruef, 2006). Our work advances theory on when variability will or will not increase, with the implications of industry-level innovation variability remaining an important area for additional work (Tripsas, 1997; Greve and Rao, 2006).

Variability in Organizational Performance Advantage

We hypothesized that performance advantages associated with an administrative innovation would diverge over time under the boundary conditions of our empirical setting. Our results clearly refute this prediction. Instead, findings match the learning models in which increasing levels of implementation experience lead to increasing performance levels coupled with decreasing performance variability (Yelle, 1979; March, 1991; Argote, 1999). This result, when combined with results for our first hypothesis, offers the unexpected finding of increased variability in one industry-level learning outcome while decreased variability for another.

Variability was reduced and by the later industry period, implementing clubs increased their performance mean when competing against non-implementers. The direct, head-to-head competitive measures of performance advantage used here mean that one can reasonably conclude this performance increase reflects true execution behavior on the field. The disruptions and pathologies for organizations learning were not sufficient to produce variability in this performance.

Why did variability occur in the innovation feature, but not in the performance outcomes, while mean performance increased? We see two major candidates as explanations for this pattern. First, a strong impact of deliberate experimentation—one form of learning from own experience—is consistent with our results for both our hypotheses. High levels of ongoing experimentation should produce varying innovation features over time consistent with our first hypothesis (March, 1991). At the same time, equifinality arguments suggest that multiple configurations of innovation features can be performance enhancing. If the ongoing experimentation is effective, it should permit organizations to improve their performance while they hone in on different farm-system sizes. Second, deliberate selective vicarious learning from multiple targets could also produce both greater later variation in size coupled with increasingly similar performance. This would occur if clubs were able to select more appropriate targets for vicarious learning, or switch to more fruitful imitation strategies over time. Effective experimentation and improved selective vicarious learning could allow clubs to improve their performance in different ways. As clubs get closer to the maximum performance advantage the innovation can offer, their relative performance difference can decline.

If this speculation has validity, the focal learning processes do not have value through unearthing a universally valuable implementation approach. Instead they lead to matching the organization's implementation approach to its specific local setting and constraints. At first blush it seems obvious that an innovation will be most effective when it is implemented with ongoing adjustment to local conditions. However, this assumption is seriously contested both theoretically and in practice. Tailoring an innovation to local contexts can also lead to deteriorating outcomes (Winter and Szulanski, 2001; Ansari, Fiss, and Zajac, 2010; Winter et al., 2011). Future work teasing out how our results relate to this important research frontier would have obvious value.

The overall pattern of our results also seems much less consistent with two other potential variance-inducing contingency factors. First, it seems less likely that epistasis or high interdependence between different innovation features played a major role here. In the presence of high epistasis, ongoing experimentation with different innovation features should produce high variance performance outcomes (Becker and Gerhart, 1996; Levinthal, 1997; Axelrod and Cohen, 2001). Our results are more consistent with different innovation features beyond farm-system size, such as scouting, recruiting, training, and selection practices, each had some independent value on their own. In this case, ongoing experimentation or selective imitation could permit clubs to gradually improve related performance advantages rather than experience varying spikes and drops in performance outcomes (Brown and Eisenhardt, 1997; Axelrod and Cohen, 2001).

Second, the pattern of our results is not consistent with an important role for the variance-inducing effect of a winner-takes-all incentive structure. March (1991) argued that although organizations will usually take too little risk in learning, high-outcomes-only incentive systems will induce them to take extreme risks and result in high performance variability. MLB clubs had strong competitive motivations but had to show reliable superior performance in over 150 regular season games to make it to the playoffs. Thus, MLB clubs operated in a payoff setting that rewarded reliable competitive performance rather than extreme outcomes only. Consistent with this argument, results were different for research in the movie industry, which rewards novelty and extreme performance in high-budget films (Hozic, 2001; Miller and Shamsie, 2001). Miner, Haunschild and Schwab (2003) reported that for high-budget movie projects, repeated collaboration with the same contributors—a form of increasing shared experience—led to significantly higher performance variability in both box-office revenue and Oscar nominations. Consequently, the lack of support for divergence in innovation-related performance advantages could be a direct result of the MLB industry's incentive structure.

Towards Contingency Models of Industry-Level Divergence and Convergence

Our results may at first seem consistent with what current organization theory already predicts. Careful reflection strongly suggests otherwise. Imagine we had found the opposite pattern with reduced variability in the administrative innovation feature, but increased or sustained variability in performance. If organizations learn of what to do as a way to achieve legitimacy (Suchman, 1995) but also face deep problems in connecting actions to useful outcomes (Levitt and March, 1988), we would expect such a pattern (Meyer and Rowan, 1977). This seemingly obvious pattern is, of course, the precise opposite of what is found here: there is no convergence in the administrative innovation feature we examine but there is convergence in organizational performance advantage.

The totality of our results advances contingency theories of convergence and divergence in three ways. First, our theory and findings highlight that learning processes can produce both industry-level convergence and divergence under plausible assumptions. Second, our results highlight that different patterns can appear for different learning outcomes such as implemented innovation features and performance outcomes. This suggests the importance of identifying contingency factors specific to types of learning outcomes. Third, while we do not measure specific contingency factors, the pattern of results is more consistent with some factors playing roles than others in this setting. Our results for our first hypothesis were consistent with a potential impact of all four variability-inducing factors including: (1) continuing deliberate experimentation, (2) varying targets and strategies in vicarious learning, (3) interdependence between the impact of different components of an innovation, and (4) the interaction between levels of learning (Miner, Haunschild, and Schwab, 2003). The combined results for our hypotheses seemed more consistent with selective vicarious learning and direct learning through experimentation.

Limitations, Rival Interpretations and Further Research

The stability of our study's context has the advantage or ruling out potential alternative explanations, but the stability may also represent an important boundary condition for our theory and findings. Our study also draws attention to other potential scope conditions for the reported learning processes. High transparency across organizations supported vicarious learning and relatively clear organizational performance goals and feedback supported learning from own experiments (Levinthal and March, 1993). Our qualitative data illustrated these contextual conditions. Additional theoretical and empirical work on such scope conditions has obvious promise.

However, as the learning processes we investigated are fundamental and relevant in most industries, we expect our findings to have implications for implementation learning related to administrative innovations in many industries. For example, our findings should generalize to military organizations and franchise systems because they are quite similar with regard to transparency, stability and homogeneity of the learning units. However, we consider our findings to also have implications for implementation learning in industry settings with lower levels of transparency, stability and homogeneity, such as online banking among retail banks, POS scanning technology among mass retailers, and computer-based arbitrage trading among investment banks. The additional challenges for effective experimentation and vicarious learning in these settings may actually enhance related variance-inducing effects. We do not test issues related to these potential boundary conditions directly, therefore, extending our theory and findings to less transparent and less stable settings represents another promising domain for future work.

Methodologically, this paper contributes to learning research by using a powerful measure of organizational performance advantage based on head-to-head competition, as opposed to work that collapses performance against individual competitors into such single global measures as annual financial profitability or organizational survival (March and Sutton, 1997). At the same time, similar to traditional learning curve work, our quantitative models did not directly measure specific learning processes. Further, because of modeling constraints, we use a comprehensive, simple proxy for industry implementation experience. Our support for industry-level divergence and convergence provides a solid basis and motivation for more in-depth future research on specific learning processes and more detailed measures of implementation experience.

Theoretical development of population-level learning has stalled to some degree in our view because researchers have primarily focused on one of two different types of industry-level change potentially driven by experience. The most intuitively appealing thread which refers to change in collective norms or practices has drawn the majority of the research attention (Miner and Anderson, 1999). In our study, industry-wide changes in governing rules and norms for the farm-system innovation represent this type of population-level learning. The other less popular thread of population-level learning work emphasizes changes in the distribution of practices and routines in a population of organizations (Haunschild and Miner, 1997; Miner and Anderson, 1999). Early work on population-level learning suggested populations may not follow the same patterns of convergence as do individual organizations and that this can have important adaptive implications (Miner and Haunschild, 1995). In this study, the change in distribution of farm-system size reflects this second type of population-level learning, which is a separate issue from the change in rules related to the innovation. The important potential outcomes of industry-level variability highlight the relevance of continuing work on the mechanisms and contingency factors that enhance or suppress industry-level variability in innovation features and outcomes.

Conclusion

Our theoretical framework considers conditional perspectives on when learning activities will generate variability of aggregate learning outcomes in an industry or population of organizations. Our paper implies that learning can produce divergence rather than convergence at the industry-level but patterns for innovation features and performance outcomes can follow different trajectories. Our study encourages future research on such contingency factors which are interesting in their own right but also can have important long-term implications for industry survival and prosperity.

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TABLE 1

Means, Standard Deviations, and Correlations for Dependent Variables and Independent Variables for Seasonal Datset (N=106)

Variables	Mean	S D	Min	Max	1	2	3	4	5
1 Farm-System Size	8.54	5.90	3.00	31.00	1.000				
2 Farm-System Size in Period 2 (Dummy Variable)	0.82	0.39	0.00	1.00	0.240	1			
3 Population Difference	2.51	2.57	0.43	7.45	-0.066	0.087	1.000		
4 One Club Diff. in # of Clubs in Same City	0.44	0.50	0.00	1.00	0.138	-0.029	-0.361	1.000	
5 Two Club Diff. in # of Clubs in Same City	0.21	0.41	0.00	1.00	0.005	0.057	0.952	-0.457	1.000
6 League Dummy	0.47	0.50	0.00	1.00	0.197	0.097	0.038	0.146	0.076

N = 106

Note: Any correlation larger than 0.19 is statistically significant (two tailed).

TABLE 2

Mean Farm-System Size and Farm-System Size Variance at Clubs with Farm Systems

	All Organizations		All Organizations			Recent Farm-System Adopters[a)]	
	Period 1 (1927-1933)	Period 2 (1934-1940)	Period 3 (1926-1930)	Period 4 (1931-1935)	Period 5 (1936-1940)	Period 1 (1927-1933)	Period 2 (1934-1940)
Mean Farm-System Size	5.53	9.20	4.82	5.92	9.88	4.00	6.46
t-Test for Mean Differences	Period 1 ≠ Period 2: t=4.43 ***		Period 3 ≠ Period 4: t=1.50 † Period 4 ≠ Period 5: t=4.12 *** Period 3 ≠ Period 5: t=5.62 ***			Period 1 ≠ Period 2: t=4.87 ***	
S.D. of Farm-System Size	2.12	6.25	1.54	2.86	6.54	0.87	2.87
F-Test for S.D. Differences	Period 1 ≠ Period 2: F=4.91 *		Period 3 ≠ Period 4: F=1.26 Period 4 ≠ Period 5: F=5.17 * Period 3 ≠ Period 5: F=2.84 †			Period 1 ≠ Period 2: F=5.83 *	
Coefficient of Variation	0.38	0.68	0.32	0.48	0.66	0.22	0.44
n	19	87	11	25	72	9	48

NOTE: Analyses used seasonal data because farm-system size varies across seasons only; limted to teams with farm systems; all t-tests assume unequal variances in subsamples; S.D. differences were analyzed using robust F-test based on 10%-trimmed mean as proposed by Brown and Forsythe (1974) that accounts for differences in group size and moderate deviations from normality.

a) Organizations with a maximum of four years of direct farm-system implementation experience.

Two-tailed tests: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

TABLE 3
Multi-Level Mixed-Effect Regression of Farm-System Size in the U.S. Baseball Industry, 1927-1940

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Estimation Procedure	REML	REML	MLE	REML	REML
Autocorrelation Correction (AR 1)	No	No	No	Yes	No
Organizations in Sample	All Adopter	All Adopter	All Adopter	All Adopter	Recent Adopters [a)]
FIXED EFFECTS					
Constant	3.611	5.405 **	5.599 **	6.526 *	5.091 **
Population Difference	-0.586	-0.643	-0.846	-1.299	-0.714
Two Club in Same City	-0.224	0.059	0.244	1.766	-0.247
Three Clubs in Same City	3.701	3.387	4.699	9.611	3.581
League Dummy	0.144	2.348	2.140	1.593	0.359
Farm-System in Time Period 2	5.856 ***	3.034 †	3.127 *	0.958	2.351 *
	(1.724)	(1.606)	(1.476)	(1.600)	(1.151)
RANDOM EFFECTS					
	Identity	Independent	Independent	Independent	Independent
sd(Constant)	3.512	0.024	0.001	0.001	0.001
	(0.795)	(7.185)	(0.001)	(0.001)	(0.001)
sd(Farm-System in Time Period 2)	3.512	4.820	4.236	0.381	1.239
	(0.795)	(1.094)	(0.908)	(7.484)	(0.591)
sd(Residual)	3.707	3.691	3.635	6.021	2.440
	(0.284)	(0.281)	(0.330)	(0.976)	(0.264)
Log restricted likelihood	-297.78	-296.66	-303.95	-272.85	-129.07
Δ Log Likelihood		1.12			
Log Likelihood Ratio Test (χ^2)		2.24 †			
Groups	16	16	16	16	16
n	106	106	106	106	57

NOTE: Standard errors that account for lack of error independence for same club.

a) Organizations with a maximum of four years of direct farm-system implementation experience.

Two-tailed tests: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

TABLE 4

Means, Standard Deviations, and Correlations for All Variables Based on Difference Scores from Matched Team Pairs

Variable	Mean	S D	Min	Max	1	2	3	4	5	6	7
1 Team Performance (DV)	0.50	0.15	0.05	0.95	1.00						
2 Farm-Team System Advantage in Time Period 1	0.07	0.27	0.00	1.00	0.05	1.00					
3 Farm-Team System Advantage in Time Period 2	0.15	0.35	0.00	1.00	0.29	-0.12	1.00				
4 Population Difference	0.27	3.48	-7.00	7.00	0.23	-0.16	0.05	1.00			
5 One Club Diff. in # of Clubs in Same City	0.08	0.75	-1.00	1.00	-0.02	-0.08	-0.07	0.54	1.00		
6 Two Club Diff. in # of Clubs in Same City	0.02	0.35	-1.00	1.00	0.10	-0.05	0.03	0.62	-0.06	1.00	
7 League Dummy	0.50	0.50	0.00	1.00	0.07	0.09	-0.07	-0.02	-0.02	0.13	1.00
8 Reserve Team	0.01	0.52	-1.00	1.00	0.21	0.23	0.02	0.01	-0.07	0.00	0.05

N = 1008

NOTE: Farm-Team System in Time Period 1 and Farm-Team System in Time Period 2 dummy coded with Team with Farm-Team System always being first team in the matched pair. The League Dummy identifies of the matched pair is either from the American League or the National League. All other control variables are contrast coded and based on the difference scores of each matched-team pair. Any correlation larger .061 is statistically significant (two-tailed).

TABLE 5
Mean Performance and Performance Variance at Teams with Farm Systems

	All Organizations		All Organizations			Recent Farm-System Adopters[a)]	
	Period 1 (1927-1933)	**Period 2 (1934-1940)**	**Period 3 (1926-1930)**	**Period 4 (1931-1935)**	**Period 5 (1936-1940)**	**Period 1 (1927-1933)**	**Period 2 (1934-1940)**
Mean Performance	0.53	0.61	0.56	0.56	0.61	0.52	0.61
t-Test for Mean Differences	Period 1 ≠ Period 2: t=3.71 ***		Period 3 ≠ Period 4: t=0.02 Period 4 ≠ Period 5: t=2.08 * Period 3 ≠ Period 5: t=1.39			Period 1 ≠ Period 2: t=5.17 *	
S.D. of Performance	0.17	0.13	0.03	0.02	0.01	0.17	0.12
F-Test for S.D. Differences	Period 1 ≠ Period 2: F=6.78 **		Period 3 ≠ Period 4: F=0.14 Period 4 ≠ Period 5: F=4.20 * Period 3 ≠ Period 5: F=3.91 *			Period 1 ≠ Period 2: F=1.85 *	
Coefficient of Variation	0.32	0.21	0.05	0.03	0.02	0.33	0.21
n	75	148	35	73	115	54	62

NOTE: Analyses used pairs data because it represents most refined performance measure; limted to teams with farm systems; farm-team performance effects are lagged by four years; all t-tests assumed unequal variances in subsamples; S.D. differences were analyzed using robust F-test based on 10%-trimmed mean as proposed by Brown and Forsythe (1974) that accounts for differences in group size and moderate deviations from normality.

a) Organizations with a maximum of four years of direct farm-system implementation experience.

Two-tailed tests: † p < .10; * p < .05; ** p < .01; *** p < .001

TABLE 6
Multi-Level Mixed-Effect Regression on Farm-System Performance Advantage in Head-to-Head Competition Between Matched Pairs of U.S. Baseball Clubs

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Log-Transformed DV	No	No	No	No	No	Yes	Yes	Yes	No	Yes
Autocorrelation Correction (AR 1)	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes
Estimation Procedure	REML	REML	MLE	REML	REML	REML	REML	REML	REML	REML
Time Periods	1923-1940	1923-1940	1923-1940	1923-1940	1927-1940	1923-1940	1923-1940	1927-1940	1923-1940	1923-1940
Organizations in Sample	All Teams	All Teams	All Teams	All Teams	All Teams	All Teams	All Teams	All Teams	Recent Adopters [a)]	All Teams
FIXED EFFECTS										
Constant	0.472 ***	0.473 ***	0.473 ***	0.467 ***	0.471 ***	-0.810 ***	-0.821 ***	-0.816 ***	0.435 ***	0.473 ***
Population Difference	0.021 ***	0.020 ***	0.020 ***	0.021 ***	0.018 ***	0.045 ***	0.047 ***	0.039 ***	0.024 ***	0.020 ***
One Club Diff. in # of Clubs in Same City	-0.050 ***	-0.049 ***	-0.049 ***	-0.048 ***	-0.039 **	-0.107 ***	-0.108 ***	-0.084 **	-0.052 ***	-0.049 ***
Two Club Diff. in # of Clubs in Same City	-0.091 ***	-0.089 ***	-0.090 ***	-0.096 ***	-0.065 *	-0.200 ***	-0.219 ***	-0.141 *	-0.114 ***	-0.091 ***
League Dummy	0.028 +	0.025 +	0.026 +	0.028 +	0.025	0.067 *	0.072 *	0.065 +	0.035 *	0.028 +
Reserve Team	0.036 ***	0.035 ***	0.036 ***	0.037 ***	0.036 ***	0.084 ***	0.089 ***	0.091 ***	0.034 ***	0.037 ***
Difference in Years of FT Experience										0.005 +
Farm-System Advantage in Time Period 1	0.025	0.017	0.018	0.028	0.026	0.050	0.067	0.068	0.027	0.009
	(0.023)	(0.028)	(0.027)	(0.028)	(0.027)	(0.054)	(0.055)	(0.051)	(0.031)	(0.028)
Farm-System Advantage in Time Period 2	0.097 ***	0.099 ***	0.100 ***	0.117 ***	0.115 ***	0.205 ***	0.242 ***	0.241 ***	0.079 ***	0.089 ***
	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.030)	(0.029)	(0.030)	(0.018)	(0.015)
RANDOM EFFECTS										
sd(constant)	0.037	0.037	0.034	0.045	0.054	0.077	0.096	0.115	0.039	0.039
	(0.009)	(0.009)	(0.008)	(0.007)	(0.008)	(0.019)	(0.015)	(0.017)	(0.009)	(0.008)
sd(Farm-System Advantage in Time Period 1)	0.051	0.084	0.079	0.091	0.077	0.122	0.140	0.101	0.092	0.085
	(0.017)	(0.028)	(0.027)	(0.026)	(0.027)	(0.074)	(0.061)	(0.073)	(0.032)	(0.028)
sd(Farm-System Advantage in Time Period 2)	0.051	0.029	0.023	0.047	0.039	0.001	0.024	0.001	0.001	0.028
	(0.017)	(0.028)	(0.032)	(0.018)	(0.022)	(0.001)	(0.135)	(0.001)	(0.001)	(0.028)
sd(Residual)	0.130	0.130	0.130	0.126	0.127	0.306	0.300	0.115	0.131	0.130
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.008)	(0.007)	(0.017)	(0.004)	(0.003)
Log Restricted Likelihood	603.23	604.67	633.85	579.55	436.81	-247.21	-269.33	-220.93	497.84	601.19
Δ Log Likelihood		-1.44								
Log Likelihood Ratio Test (χ^2)		2.89 †								
Δ sd(Farm-Syst. Adv. P1) and sd(Farm-System Adv. P2)	0.000	-0.056 **	-0.056 **	-0.044 **	-0.038 **	-0.121 **	-0.116 **	-0.100 **	-0.091	-0.057 **
N	1008	1008	1008	1008	784	1008	1008	784	817	1008

NOTE: Fram-team performance effects are lagged by four years; standard errors account for lack of error independence within same matched pair.

a) Organizations with a maximum of four years of direct farm-system implementation experience.

Two-tailed tests: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 1
Farm-System Size of Individual Major League Baseball Clubs

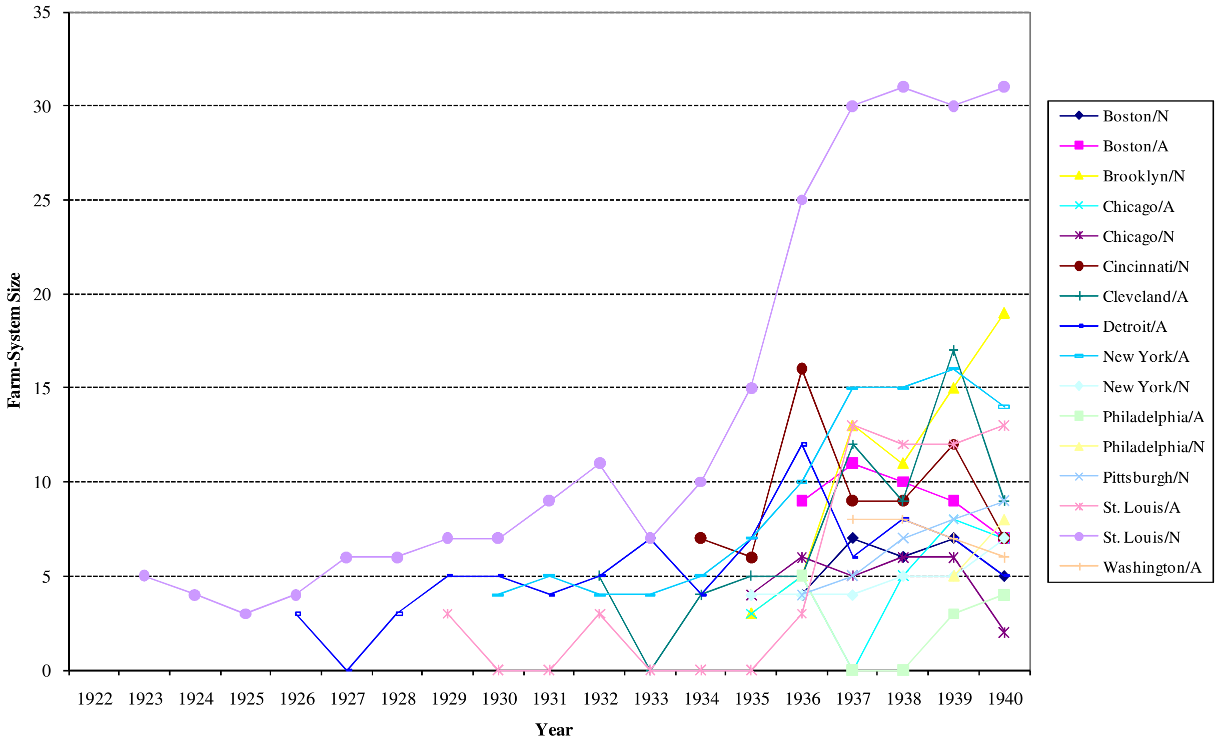

Figure 2
Average Farm-System Size and S.D. of Farm-System Size, 1923-1940

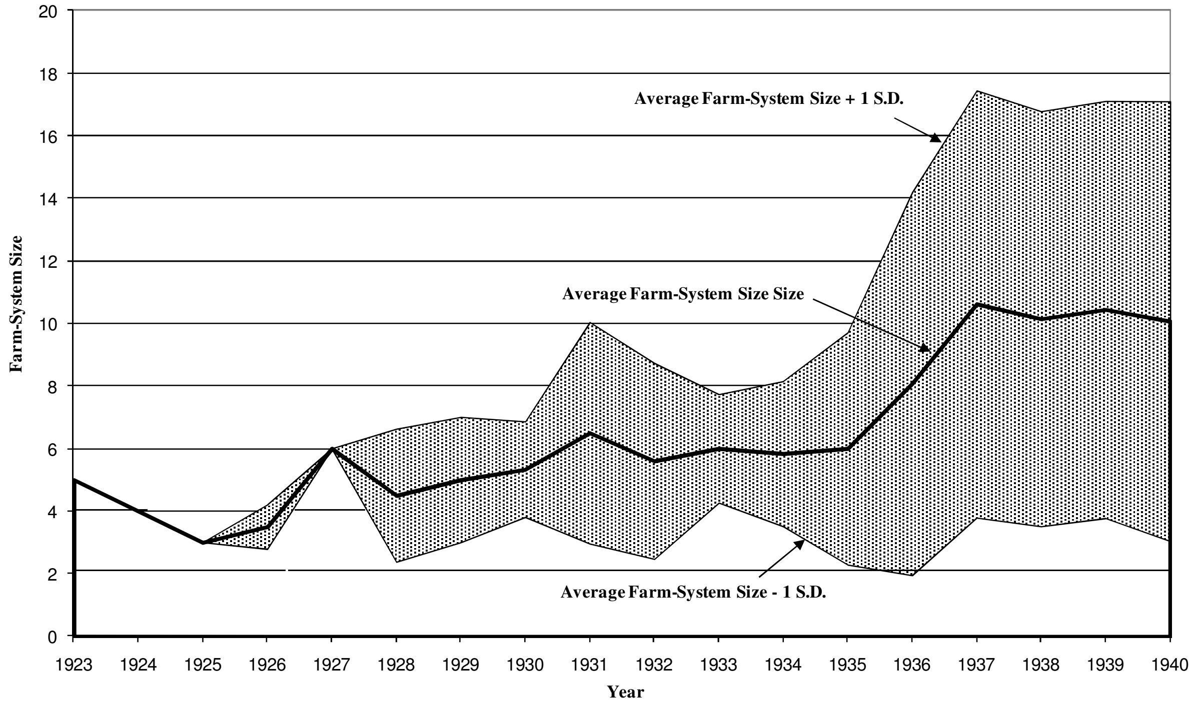

Figure 3
Average Farm-System Performance Advantage and S.D. of Farm-System Performance Advantage, 1923-1940