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Aspiration Performance and Railroads' Patterns of Learning from Train Wrecks and Crashes

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We link two influential organizational learning models—performance feedback and experiential learning—to advance hypotheses that help explain how organizations' learning from their own and others' experience is conditioned by their aspiration-performance feedback. Our focus is on learning from failure; this kind of learning is essential to organizational learning and adaptation, and a necessary complement to studies of learning from success. Our analysis of U.S. Class 1 freight railroads' accident costs from 1975 to 2001 shows that when a railroad's accident rate deviates from aspiration levels, the railroad benefits less from its own operating and accident experience and more from other railroads' operating and accident experiences. These findings support the idea that performance near aspirations fosters local search and exploitive learning, while performance away from aspirations stimulates nonlocal search and exploration, providing a foundation for constructing more-integrated models of organizational learning and change.

Key words: organizational learning; aspiration performance; accident reduction

Introduction

A central idea in organizational learning theory is that organizations learn from experience and make changes to practices, strategies, and structures conditional on their performance (Cyert and March 1963, Huber 1991, Levitt and March 1988). This idea has led to an interest in how organizational performance improves with experience (Argote et al. 1990, Lapré et al. 2000, Pisano et al. 2001, Thompson 2001) and in how feedback regarding organizational performance relative to aspirations—a reference point that distinguishes organizational success and failure—affects the likelihood of different types of action (Greve 1998, March 1988, Miller and Chen 1994, Ocasio 1995). Surprisingly, despite the common origins of experiential learning and performance feedback models from the behavioral theory of the firm, the link between these two models has not been explored: how organizations' patterns of learning from experience are influenced by aspiration-performance feedback. This gap in the learning literature is the focus of our study.

Experience is fundamental to learning (Cyert and March 1963, Huber 1991); learning by doing is widely held to be a source of organizational knowledge, capabilities, and improved organizational performance (Argote et al. 1990). Numerous experience-curve or learning-curve studies demonstrate that the unit cost of production decreases with cumulative production experience (Argote 1999, Yelle 1979) and that product quality increases with calendar time (Levin 2000). Learning curves are influenced not only by organizations' own direct experiences, but also by their vicarious experiences of other organizations (Baum and Ingram 1998, Haunschild and Sullivan 2002, Ingram and Simons 2002, Lester and McCabe 1993, Thornton and Thompson 2001, Zimmerman 1982).

In learning curve research, however, the role of organizational performance (to improve performance beyond current levels) is implicit. Learning theories also suggest, however, that decision makers' patterns of learning and action depend on the extent to which their organizations' performance differs from their aspiration levels (Cyert and March 1963, Greve 2003). Aspiration-performance feedback models emphasize how perceptions of success and failure motivate change: satisfactory outcomes that meet aspirations foster local search of old certainties that reinforce and refine lessons drawn from earlier experience; outcomes that fail to meet or exceed aspirations stimulate nonlocal search for new possibilities to correct or further enhance performance (Cyert and March 1963, Levitt and March 1988, March and Shapira 1992).

Performance feedback, therefore, seems essential to understanding conditions under which organizations emphasize experiential or vicarious learning from their own or others' experience, respectively. Surprisingly, however, how organizations' learning is conditioned by performance feedback has received little empirical attention. In this study, therefore, we explicitly link organizations' performance feedback with experiential learning. In particular, we specify the effects of organizations' aspiration-performance feedback on patterns of learning from own and others' experience. Our key prediction is that performance feedback triggers different search strategies: organizations emphasize learning from their own experience when performance is near aspirations, and emphasize learning from others' experience when performance deviates from aspirations. Our theory speaks directly to patterns of managerial attention and the balance between experiential and vicarious learning under different performance conditions. By connecting performance feedback and learning-curve models in this way we move toward integrating these two perspectives, which are core to organizational adaptation, and which are compatible in their core assumptions and interests.

We examine the relationship between performance feedback and learning from experience using annual data on U.S. Class 1 freight railroads' accidents from 1975 to 2001. This setting provides an opportunity to examine organizations' learning from their own and each others' cumulative operating and accident experience. Compared to operational successes, train accidents are relatively low-frequency events that represent significant and salient failures for the firm or firms involved. The average railroad in our sample experienced roughly one accident every 93,000 operating miles, or 399 accidents, costing $19.4 million per year (in 1988 dollars; all dollars in this paper are U.S. dollars, unless indicated otherwise). The complex causes of railroad accidents (Evans 2000) suggest that learning from them is likely to be fallible, making cumulative experience valuable.

Our focus on accidents contributes to the further development of the emerging experiential learning-from-failure perspective (Chuang and Baum 2003, Denrell 2003, Haunschild and Rhee 2004, Haunschild and Sullivan 2002, Kim 2000, Miner et al. 1999), which complements the large body of work emphasizing learning from success. It also complements the stream of qualitative research on high reliability organizations (HROs) (Starbuck and Farjoun 2005, Perrow 1984, Roberts and Rousseau 1989, Rochlin 1993, Starbuck and Milliken 1988, Vaughan 1996). HROs' complex, interactive technologies—space shuttles, aircraft carriers, nuclear power generation plants, and air traffic control systems—are prone to catastrophic failure, the scale of which prohibits learning through experimentation (Weick et al. 1999, Weick and Sutcliffe 2001). Although freight railroads are not HROs, as Weick et al. (1999) point out, the adaptive characteristics exhibited by effective HROs might usefully be made more central to research on organizational learning. Conversely, patterns of learning exhibited by non-HROs might usefully inform research on HROs; after all, we cannot conclude that HROs behave differently without understanding how non-HROs respond to failures.

Following the learning-curve tradition, by *learning* we refer to organizational processes that result in a subsequent performance improvement. Focusing on failure, we measure learning in terms of accident cost reductions and consider cumulative accident experience as well as cumulative operating experience as proxies for learning (Haunschild and Rhee 2004). We also follow the tradition in performance feedback research, specifying both historical performance relative to oneself, and social performance relative to comparable organizations (Greve 1998, 2003). In contrast to traditional performance metrics such as market share or return on assets, we operationalize railroads' aspiration performance based on their accident rates, which are more likely to influence learning efforts to mitigate accident costs.

Experiential Learning from Own and Others' Experience

For almost 50 years, organizational learning theorists have characterized organizations as history-dependent systems that adapt incrementally to past experience (March and Simon 1958, Lindblom 1959, Cyert and March 1963). Of course, experience is an imperfect teacher. While the popular management literature emphasizes the promise of organizational learning, organizational learning theorists repeatedly assert the difficulty of learning from experience (Levitt and March 1988, Levinthal and March 1993). An organization may be unable to learn due to paucity or ambiguity of experience, or because it has an abundance of experience, but is influenced by that experience to make the wrong decision.

Within the experiential learning frame, organizations attempt to adapt to their environments through a process of searching for alternatives. Search is conceptualized as a problem of allocating attention and resources between exploiting existing routines and exploring new ones (March 1991, Levinthal and March 1993). *Exploitation* enhances organizational functioning by reducing variability in task performance; *exploration* refers to processes of nonlocal search: identifying new ways to do things and new things to do. An organization that engages in too much exploitation can become narrow and stagnate; an organization that engages in too much exploration can become unfocused and unable to harvest the value of its current routines.

March (1991) advocates that organizations strike a balance between the two. Typically, however, obvious payoffs from improvements in areas of prior experience limit organizations' exploration of new approaches, which is risky and might jeopardize the efficiency of current operations (March 1991, Miner 1994, Nelson and Winter 1982). Search for new alternatives is thus typically conducted locally, within the neighborhood of practices that have evolved in an organization; as a result, organizations' actions tend to replicate the current state (Cyert and March 1963, Nelson and Winter 1982, Levitt and March 1988). As Levinthal and March (1993, p. 97) put it: "The effectiveness of learning in the short run and in the near neighborhood of current experience interferes with learning in the long run and at a distance." Consistent with organizations' predicted focus on exploitation, research has documented a robust phenomenon known as the *experience, or learning, curve*: as organizations gain experience producing a given output, their cost or time to produce it (or both) decreases, although at a decreasing rate. Learning is attributed to an increased awareness of how to reduce redundancies and inefficiencies through continuous refinement and adaptation of internal practices and processes in an organization's areas of expertise (Yelle 1979, Argote 1993).

An organization's own experience is not the only opportunity for learning, however. Organization theorists have long contended that organizations also learn from the experiences of other organizations. This more-exploratory learning mode is most likely to be prevalent when an organization's own experience provides inadequate guidance for dealing with new challenges or opportunities (March 1991, Miner and Haunschild 1995), so organizations turn to observation and selective imitation of other organizations' behaviors and technologies (Baum and Ingram 1998, Lieberman and Montgomery 1988). The value of others' experience for learning depends on comparability; the more comparable the organizations, the more similar the situations they face, and the greater the potential relevance of their experience to the observer (Baum et al. 2000, Greve 1998). As decision makers look for role models, they focus on comparable organizations facing similar situations (Lant and Baum 1995, Porac et al. 1995). A growing body of research demonstrates the impact of the experience of other comparable organizations on learning curves (Foster and Rosenzweig 1995, Irwin and Klenow 1994, Lester and McCabe 1993, Thornton and Thompson 2001).

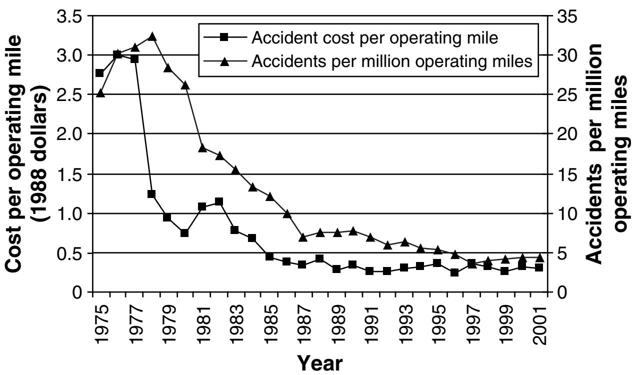
Research on organizational learning from own and others' experience emphasizes successful operations over the errors and failures that invariably accompany success (Miner et al. 1999). While traditional learning curves for productivity often consider the costs of failures such as rework on assembly lines or downtime costs for power plants (Lester and McCabe 1993), they do not consider direct effects of failure on learning curves. It has long been known in engineering and science that failure can be far more valuable than success for learning (Popper 1959, Petroski 1994); this is a view echoed by those concerned with sample-selection biases in organizational learning (March 1991). Causal inference requires both repetition and the opportunity to link actions to both positive and negative outcomes.

Reflecting these concerns, a learning-from-failure perspective has emerged (Sitkin 1992, Miner et al. 1999). Qualitative studies in this area emphasize learning from catastrophic failures by HROs (Starbuck and Milliken 1988, Roberts and Rousseau 1989, Vaughan 1996, Weick and Sutcliffe 2001). For HROs, exploitation is difficult: even small changes to their complex, interactive technologies can have unpredictable effects that result in failure. In a review of this literature, Weick et al. (1999, p. 109) conclude that HROs "cope with these limits on exploitation and exploration in part through exploration of meaningful analogues. … Effective HROs, faced with infrequent failures, learn from the failures of others."

More recently, quantitative studies of failure in the learning-curve tradition have appeared. Although the majority of these studies have focused on organizations' experiential learning from their own failures (Denrell 2003, Haunschild and Sullivan 2002, Haunschild and Rhee 2004), researchers have also begun to explore vicarious learning from other organizations' failures (Chuang and Baum 2003, Kim 2000, Kim and Miner 2006). These studies reinforce the Weick et al. (1999) observation that other organizations' failures are vital to learning, because individual organizations that lack sufficient experience with failure to learn from it turn to others' failures for clues about the causes of their own problems and to learn what not to do. Indeed, because organizational failures are salient, well-publicized events that organizations' decision makers attend to naturally and that analysts and officials scrutinize intensely, the details of failures are likely to be more accessible to outsiders than the details of successes, which are often purposefully concealed (Ingram and Baum 1997).

Although in some contexts others' failures may remain hidden, when the experience is visible and salient, interpretable (or at least inferable) based on available information, and generalizable across organizations, decision makers can gain access to experience created by other organizations (Kim and Miner 2006, Miner and Haunschild 1995, Rerup 2006). In our empirical setting, the U.S. Class 1 freight rail industry, visibility, interpretability, and generalizability conditions are met. U.S. freight railroads are well aware of their accidents. Each month they must report any accident that incurs a cost of more than $6,700 (in 2002) to the Federal Railroad Administration (FRA), which maintains a central database of accident statistics. These data are publicly available at www.fra.dot.gov, together with summary statistics and operating data, permitting railroads to monitor each others' accident rates and experience. A subset of these accidents (about 10 annually) are selected and investigated by the National Transportation Safety Board (NTSB), which issues a report listing accident causes and recommends actions to involved parties (typically railroads, labor unions, rail customers, local police, local fire fighters, and governmental authorities). These reports serve as a further diffusion mechanism, providing railroads' decision makers with opportunities to learn from others' accidents from the detailed, high-quality information contained in the reports themselves or accounts of the reports, and accidents more generally, published in industry-specific and general media. Moreover, because they use the same basic technology and

Figure 1 **U.S. Class 1 Freight Railroads' Average Annual Accidents and Accident Costs**



infrastructure, railroads are all at risk of similar types of accidents.

We expect that railroads' accident costs will follow the familiar learning-curve pattern based on prior evidence of organizations' accident- and error-reducing experiential learning (Haunschild and Sullivan 2002, Haunschild and Rhee 2004), as well as the functional form of our empirical data (see Figure 1). Thus, although experience is an imperfect teacher, we expect a cumulative benefit from a railroad's own and other railroads' accidents. A railroad that has accumulated greater accident experience has had the opportunity to learn how to avoid similar accidents through training or adoption of innovative safety systems, reducing its own current accident-related costs. Since accidents represent operational failures, accumulated experience with successful operations should also contribute to a reduction in accident costs. To evaluate the role of these experiential factors empirically, we advance a baseline learning curve model estimating a railroad's current accident cost, defined as the direct accident-related costs per operating mile (measured in constant 1988 dollars),[1] as a function of (a) the railroad's own cumulative prior operating and accident experience, and (b) other railroads' cumulative prior operating and accident experience. More formally,

$$\begin{aligned}&\mathit{Accident\ Cost}_{it}\\&\quad=\beta_1\ln\sum_{\tau=t_0}^{t-1}\frac{OE_{it}}{\gamma_{t-\tau}}+\beta_2\ln\sum_{\tau=t_0}^{t-1}\frac{AE_{it}}{\gamma}+\beta_3\ln\sum_{j=1}^{n}\sum_{\tau=t_0}^{t-1}\frac{OE_{jt}}{\gamma_{t-\tau}}\\&\qquad+\beta_4\ln\sum_{j=1}^{n}\sum_{\tau=t_0}^{t-1}\frac{AE_{jt}}{\gamma_{t-\tau}}+\lambda_{it-1}+\theta_t+\varepsilon_{it},\end{aligned}\tag{1}$$

where i is the focal railroad, j includes all n railroads other than i, t_0 is the first observation year, t is the current year, $t-1$ is the prior year, OE_{it} and OE_{jt} are the operating experiences (gauged by completed operating miles) of the focal railroad and other railroads in a given year, and AE_{it} and AE_{jt} are the number of accidents experienced by the focal railroad and other railroads in a given year. Following prior work (Ingram and Baum 1997), we depreciate past experience using a discount rate, γ, which depreciates experience as a function of its age (i.e., $t-\tau$) to account for the possibility that the benefits of experience to organizations may decay over time due to forgetting and antiquation of learning (Argote et al. 1990, Argote 1993).[2]

β_1 and β_2 are coefficients for the effects of own operating and accident experience; β_3 and β_4 are coefficients for the effects of others' operating and accident experience. λ_{it-1} represents a vector of coefficients for lagged organizational control factors likely to influence a railroad's accident costs, θ_t is a vector of coefficients for year fixed effects, and ε_{it} is an error term. We expect $\beta_1 < 0$, $\beta_2 < 0$, $\beta_3 < 0$, and $\beta_4 < 0$; that is, ceteris paribus, the greater a railroad's past cumulative operating and accident experience and the greater the other railroads' cumulative operating and accident experience, the lower the railroad's current accident cost.

Aspiration-Performance Feedback and Accident Reduction

Aspiration-performance feedback models are central to learning research on organizational change (Bromiley 1991; March and Shapira 1992; Greve 1998, 2003). An *aspiration level* is a reference point that simplifies performance evaluation by transforming continuous outcome measures into discrete measures of success or failure (March and Simon 1958). Aspiration levels arise from comparisons against two reference points that decision makers use to evaluate their own current performance: the organization's own historical performance (Cyert and March 1963, Levinthal and March 1981), and recent performance of the organization's reference or peer group (Festinger 1954, Cyert and March 1963, Pfeffer and Salancik 1978).

Categorizing outcomes as successes and failures affects decision makers' willingness to learn and change. In particular, this willingness depends on whether performance is (a) distant from or near aspiration levels, and (b) above or below aspirations (March and Shapira 1992). When an organization is performing near aspirations, lessons from earlier experiences are reinforced, current efforts continue largely unchanged, and the focus of learning is on local search and minor adjustments of existing routines that promise small improvements by reducing variability in the quality or efficiency of task performance. More-exploratory actions that might jeopardize current efforts are avoided.

When an organization is performing below aspirations, its decision makers emphasize more-exploratory, nonlocal search and larger changes with the potential to raise the organization's performance closer to aspirations (Singh 1986). Performance below aspirations triggers problem-driven search, stimulating exploration of new practices and courses of action, with the extent of search and change depending on how far performance is below the aspiration point. Studies show that performance below aspirations (i.e., unsatisfactory performance) leads decision makers to initiate experimentation to identify new ways of doing things and new things to do, while satisfactory performance does not (for a review, see Greve 2003).

We might, in the accident case, expect this effect to be even stronger—it is not just the absence of good performance but also the presence of widely publicized negative events that force organizations into a search mode. Indeed, if the organization's decision makers are not motivated to search for explanations and solutions after experiencing a large number of accidents, they may be forced to explain what they will do to improve performance as regulatory and safety authorities subject them to inspections and questions, and shareholders, media, and the general public increase scrutiny. Performance problems and crises may thus raise serious questions about the legitimacy of organizational procedures and create the need to revise organizational activities to rectify existing organizational problems (Oliver 1992).

The performance-feedback model also suggests that organizations performing above their aspiration levels may engage in greater learning and change than those performing at or near their aspiration levels. This slack-driven search prediction stems from the idea that performance above aspirations leads to nonlocal search, experimentation, and change because success provides organizational decision makers with access to resources and instills confidence in their abilities to pursue new initiatives (Cyert and March 1963, Levinthal and March 1981, Lant et al. 1992, March and Shapira 1992). Although some types of high performance may not create slack resources, most types lower the cost of resources (Aldrich and Auster 1986).

In the case of freight rail accidents, performance above historical aspirations frees resources allocated to safety departments' budget costs. Performance above social aspirations lowers a railroad's direct (e.g., cleanup, and track and equipment repair) and indirect costs (e.g., insurance and litigation) and may also increase revenue if reliability increases its attractiveness to customers compared with more accident-prone railroads (Wolf 1998). Freed-up resources make it possible for railroads' safety departments to redeploy staff to preventive activities, such as increasing diagnostic track and equipment inspections; to develop and train employees in safer work practices; or to invest in new safety equipment that, for example, detects small wheel flaws that are difficult to see with visual inspection methods but that greatly accelerate track failure (Wolf 1997).

Taken together, performance feedback predictions suggest that the likelihood of organizations' decision makers engaging in nonlocal search and initiating major changes to reduce accident costs is positively related to the discrepancy between their organizations' performance and aspiration levels. Because organizations' decision makers react more strongly to threats than to opportunities (Kahneman and Tversky 1979), organizations tend to be more open to exploration and change when performance is below aspirations (Bromiley 1991, Singh 1986, Greve 1998). As a result, organizations performing below aspirations are expected to endeavor more vigorously to improve—that is, we expect a steeper relationship between performance and accident costs below than above a firm's aspiration level.

We extend Equation (1) to include main effects of performance relative to historical and social aspirations on the rate of accident cost reduction:

$$\begin{aligned} &\mathit{Accident\ Cost}_{it} \\ &\quad = \beta_1 \ln \sum_{\tau-t_0}^{t-1} \frac{OE_{it}}{\gamma_{t-\tau}} + \beta_2 \ln \sum_{\tau-t_0}^{t-1} \frac{AE_{it}}{\gamma_{t-\tau}} + \beta_3 \ln \sum_{j=1}^{n} \sum_{\tau-t_0}^{t-1} \frac{OE_{jt}}{\gamma_{t-\tau}} \\ &\qquad + \beta_4 \ln \sum_{j=1}^{n} \sum_{\tau-t_0}^{t-1} \frac{AE_{jt}}{\gamma_{t-\tau}} + \beta_5 SAP > 0_{it} + \beta_6 SAP < 0_{it} \\ &\qquad + \beta_7 HAP > 0_{it} + \beta_8 HAP < 0_{it} + \lambda_{it} + \theta_t + \varepsilon_{it}, \qquad (2) \end{aligned}$$

where $SAP > 0_{it}$ and $SAP < 0_{it}$ are railroad i's accident performance relative to social aspirations in a given year, $HAP > 0_{it}$ and $HAP < 0_{it}$ are railroad i's accident performance relative to historical aspirations in a given year, and β_5, β_6, β_7, and β_8 are coefficients for the effects of accidents relative to aspirations on accident costs. Other parameters are defined as in Equation (1).

As in prior work (Greve 1998, 2003; Lant 1992) we measure HA_{it}, a railroad's historical aspiration at time t, as a weighted moving average of its performance, $\alpha P_{it-1} + (1 - \alpha)HA_{it-1}$, where P is focal railroad i's performance, t is the time period, HA_{it-1} is the focal railroad's historical aspiration from the prior period, and α is a weight given to prior performance and historical aspirations. High values of α quickly update the historical aspiration level, emphasizing recent performance.[3] Organizations' aspiration levels are typically operationalized in terms of metrics salient to organizational decision makers, such as market share (Greve 1998), revenue (Mezias et al. 2002), return on sales (Audia et al. 2000), or return on assets (Miller and Chen 2004). Here, given our focus on accident cost reduction, we measure railroads' aspirations based on their relative historical and social accident rates, because more-general performance metrics are less likely to mitigate directly accident costs.

We measure performance relative to historical aspirations as the value of a railroad's historical aspiration level minus its number of accidents in the current year, or $HAP_{it} = HA_{it} - P_{it}$. To permit different slopes above and below the aspiration level point, HAP_{it} is split into two variables: $HAP_{it} > 0$ equals zero for observations where performance is below historical aspirations, and equals historical performance otherwise. $HAP_{it} < 0$ is zero for all observations where performance is greater than historical aspirations, and equals historical performance otherwise. $HAP_{it} > 0$ tests for slack-driven search, and $HAP_{it} < 0$ for problem-driven search.

We defined a railroad's social aspiration level based on the current performance of other railroads so the aspiration level equals others' mean performances. Thus, a railroad's social aspiration at time t is $(\Sigma_j P_{jt})/N_t$, where j is another railroad, P_{jt} is railroad j's performance at time t, and N_t is the number of other railroads, Σ_j, at time t. As with historical aspirations, the key variables are relative performance measures, defined as a railroad's social aspiration level minus its number of accidents in the current year. To allow for different slopes for values above and below aspirations, we again split social aspiration performance into two variables, $SAP_{it} > 0$ (to test for slack-driven search) and $SAP_{it} < 0$ (to test for problem-driven search).

We expect that $\beta_5 < 0$, $\beta_6 > 0$, $\beta_7 < 0$, and $\beta_8 > 0$; that is, ceteris paribus, the more a railroad's performance is above or below its historical and social aspirations at $t-1$, the more likely the railroad's decision makers are to undertake changes to reduce their accident costs.

Experience × Aspiration-Performance Interactions

To this point, we have considered learning-curve and aspiration-performance models independently, yet there is a correspondence between learning from own and others' experience in the learning-curve model and local and nonlocal search in the performance-feedback model: learning from own experience is a form of local search, or exploitation; learning from others' experience is a form of nonlocal search, or exploration. This correspondence suggests a fundamental connection between the two learning models.

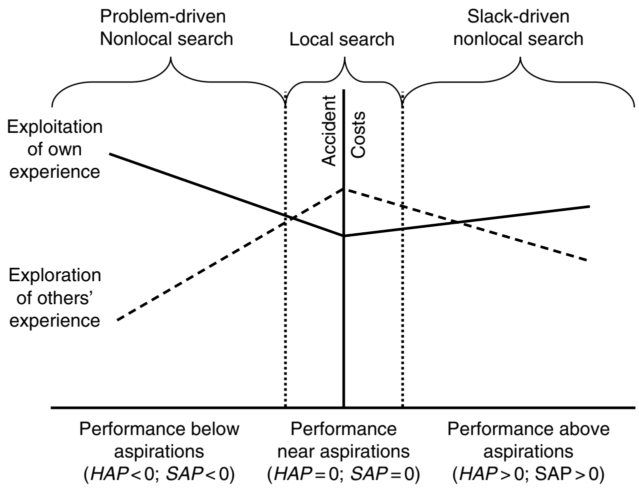
The learning-curve model emphasizes exploitive learning from own experience and exploratory learning from others' experience, but does not specify mechanisms affecting the balance between the two. The aspiration-performance model, which predicts the type of search behavior (local or nonlocal) initiated by decision makers, appears to specify precisely such a mechanism. The key aspiration-performance prediction is that, while achieving aspirations leads to local search reinforcing old certainties, performance discrepant from aspirations stimulates nonlocal problem- or slack-driven search for new ways to enhance practices. This prediction suggests that when performing near aspirations organizations will emphasize exploitation of lessons drawn from their own past experience, while when failing to achieve or exceed aspirations, exploration for novel solutions from other organizations' experience will receive greater attention.

Although organizations make incremental adjustments based on observations of other organizations, and conversely, engage in internal research and development (R&D) and other efforts to learn new ideas that do not necessarily rely on ideas from other organizations (Gavetti and Levinthal 2000, Levinthal and Rerup 2006, Weick and Sutcliffe 2006), such external exploitation and internal exploration are unlikely dominant modes of organizational learning. Learning from own experience tends to be exploitive. Own experience is not commonly a source of new practices and strategies, but is rather a basis on which to refine existing practices and strategies. It is also local. An organization is unlikely to find novel solutions it has not tried before in its own experience; for that, it must look to others' experience: "Thus the distance in time and space between the locus of learning and the locus for realization of returns is generally greater in the case of exploration than in the case of exploitation" (March 1991, p. 85).

Moving beyond local search requires exploration across organizational or technological boundaries, or both (Rosenkopf and Nerkar 2001). An organization engages in nonlocal search when it looks beyond its own experience for ideas and solutions it has never tried before. Learning from others' experience is more likely to entail learning new practices, partly because the diversity of practices is far greater beyond than within an organization's boundaries. This diversity comes about despite individual organizations' tendency to focus on refining current practices, because different organizations pursue refinement of different practices (Levinthal and March 1993, Miner and Haunschild 1995). Learning from others' experience is also more likely to entail learning new practices, because organizations' decision makers tend to rely on others for ideas about solutions to problems when they lack sufficient experience of their own to learn from, as is often the case when attempting to learn from failure (Ingram and Baum 1997, Weick et al. 1999).

Therefore, in addition to the main effects of experience and aspiration performance specified in Equation (2), we hypothesize that the effects on accident cost reduction from exploration (nonlocal search) of others' experience and exploitation (local search) of own experience vary as a function of performance. Specifically, conditional on the main effects, we predict that coefficients for interactions between others' operating and accident experience (OE_{jt} and AE_{jt}) and performance above aspirations ($HAP > 0_{it}$, $SAP > 0_{it}$) will be negative, while coefficients for their interactions with performance below aspirations ($HAP < 0_{it}$, $SAP < 0_{it}$) will be positive. In contrast, we predict that coefficients for interactions between own operating and accident experience (OE_{it} and AE_{it}) and performance above aspirations

Figure 2 Experiential Learning × Aspiration-Performance Interaction Hypothesis Summary



($HAP > 0_{it}$, $SAP > 0_{it}$) will be positive, while coefficients for their interactions with performance below aspirations ($HAP < 0_{it}$, $SAP < 0_{it}$) will be negative. This pattern of interactions would indicate a greater emphasis on exploration of other railroads' operating and accident experience as a source of ideas for reducing accident costs for railroads with larger performance gaps and, conversely, a greater attention to exploitation of a railroads' own operating and accident experience as a basis for lowering accident costs when performance is near aspirations.

Figure 2 graphically illustrates the hypothesized main and interaction effects. The relative slopes and magnitudes of the effects for exploitation of own experience and exploration of others' experience in the figure reflect two factors: One is that the slopes should be steeper below performance aspirations, reflecting the idea that failure tends to prompt greater change search than does success (e.g., Kahneman and Tversky 1979). The other is that the exploration of own experience curve should be steeper and lower because nonlocal search of other organizations' experience should inform the implementation of the more-extensive changes to reduce accident costs that are prompted by performance gaps.

Data and Methods

U.S. freight railroads are divided into three classes according to scale: Class 1 railroads generate freight revenues of at least $272 million (in 2002), and Class 2 railroads generate at least $40 million. Class 3 railroads include small-scale rail operations that own less than 100 miles of track (e.g., firms that own spur lines connecting their plants to main lines). Our sample includes all Class 1 freight railroads active in the U.S. from 1975 to 2001. Class 1 freight railroads dominated the U.S. industry over the period we study, accounting for more than 90% of U.S. freight rail activity ($29.7 billion in value, 1.26 trillion revenue-ton miles in volume) (NTSB 1998).

The main data for this study are operating and accident statistics reported since 1975 in the *Rail Equipment Accident/Incident Report* published by the FRA Office of Safety Analysis. In addition to basic operating statistics, this report describes collisions, derailments, and other events involving the operation of railroad on-track equipment, signals, track, or track equipment that result in damage greater than the annual dollar value serving as a reporting threshold ($6,700 for calendar year 2002). Annually, 2,500 to 3,000 new records are added to this database. Starting in 1980, these data were supplemented with data provided by the American Association of Railroads (AAR) Office of Finance on railroads' financial performance, capital expenditures, and track ownership available. Figure 1 charts the average railroad's accident cost per operating mile and number of accidents per million miles from 1975 to 2001. The figure illustrates the typical learning-curve shape, with an exponential decrease over time. Accident cost per mile over this period declined by approximately 90%, the accident rate declined by 86%.

Estimation

We estimate models based on the formulation in Equation (2) (plus interactions) on the pooled data set, with each railroad contributing a time-series panel. The dependent variable was a railroad's accident cost per operating mile, defined as the railroad's total annual accident-related costs (indexed to 1988 dollars) divided by its total annual operating miles. We entered an observation for each railroad for every year it operated from 1981 to 2001.[4] Pooling repeated observations on the same organizations violate the assumption of independence of observations, resulting in autocorrelation in the residuals. First-order autocorrelation occurs when the disturbances in one time period are correlated with those in the previous time period, resulting in incorrect variance estimates, rendering ordinary least squares (OLS) estimates inefficient and biased (Judge et al. 1985). Therefore, we estimate random-effects panel data generalized least squares (GLS) models with robust standard errors to correct for autocorrelation of disturbances due to constant firm-specific effects (Greene 2000).

Control Variables

Parameters λ_{it} and θ_t in Equation (2) are vectors of organizational control variables that may also influence a railroad's accident costs, and year fixed effects. All time-varying control variables were lagged one year to avoid simultaneity problems.

Age and Size. We measure size as operating miles and include each railroad's age to control for operating and accident experiences accumulated prior to our observation period (Haunschild and Sullivan 2002).

Accident Costs. To control for effects of accident costs on subsequent accident cost reduction, we include each railroad's total annual accident-related costs (indexed to 1988 dollars). This helps ensure that performance effects do not reflect a regression to the mean, and also helps to avoid specification bias (Jacobson 1990). We aggregated accident-related costs of other railroads to control for the possibility that industrywide costs stimulate accident reduction. Accident cost variables were logged to reduce skewness.

Net Operating Income. Financial performance may affect a railroad's access to resources as well as its decision makers' priorities and attention to safety (Milliken and Lant 1991, Rose 1993), which is why we control for annual net operating income (indexed to 1988 dollars and divided by 1 million for rescaling).

Capital Expenditures. To control for effects of capital investment in equipment, infrastructure, and management and safety systems, we control for each railroad's total annual capital expenditures (indexed to 1988 dollars and logged to reduce skewness). We aggregate capital investments of other railroads to control for the possibility that industrywide capital investment promotes accident reduction.

Miles of Own Track and Track Rights. Operating on own or others' track may influence accident rates because railroads monitor and maintain their own track, and railroads' engineers are more experienced on routes on their own tracks. We include miles of owned track and miles of other railroads' track on which a railroad has rights to operate. We aggregate the track rights of other railroads to control for the possibility that greater cross-firm track usage increases accident costs. These variables are logged to reduce skewness.

Accident Heterogeneity. Haunschild and Sullivan (2002) find that accident heterogeneity influences accident reduction rates for airlines; the more heterogeneous the causes of the accident, the higher the learning rate. Therefore, we control for both own and other railroads' accident heterogeneity, computed using a Herfindahl index based on counts of accident disaggregated by four accident causes assigned by the FRA: track, equipment, highway crossing, and human error. For ease of interpretation, we subtract the index from one, reversing the scale so that heterogeneity increases as the index approaches one.

Left Censored. Railroads established prior to 1975 will have accumulated operating and accident experience prior to our observation period that may contribute to lowering their accident rate. In addition to railroad age, to control for this unobserved experience we include a dummy variable coded one for railroads founded prior to 1975 and zero for all other railroads.

Year Fixed Effects. Finally, to control for effects of the passage of time and other environmental changes and variation over the observation period, we include a set of dummy variables for year in all our models (2001 was excluded as a base year).

Descriptive statistics are summarized in Table 1. In general, the correlations among the variables are low to moderate, although correlations among the operating and accident experience variables and several of the control variables are high. Such levels of multicollinearity among explanatory variables can result in less-precise parameter estimates (i.e., larger standard errors) for the correlated variables, but will not bias parameter estimates (Greene 2000, Kennedy 1992). So, although this does not pose a serious estimation problem, it can make it more difficult to draw inferences about the effects of adding particular variables to the models. Therefore, when building our models we followed a strategy of estimating hierarchically nested models to check that multicollinearity was not causing less-precise parameter estimates, and suppressing the significance of some variables (Kmenta 1971). We did detect some multicollinearity decreasing the efficiency of our estimates, but this did not materially affect our ability to draw inferences from the estimates.

Results

Table 2 reports random effects GLS estimates of U.S. freight railroads' accident costs per operating mile. Model 1 is the baseline model, which includes the control variables. Model 2 introduces the main effects of operating and accident experience and social and historical aspiration performance. Coefficients for own operating experience and others' accident experience are significant and negative. Given the logarithmic experience specifications, this means that railroads' accident costs decline at a decreasing rate with increases in their own operating experience and other railroads' accident experience. Coefficients for own accident experience and others' operating experience, in contrast, are significant and positive. This indicates that railroads' accident costs increase, although at a decreasing rate, with increases in their own accident experience and other railroads' operating experience.

The pattern of own experience coefficients in Table 2 suggests that, while organizations learn how to reduce accident costs from their cumulative operating experience, they do not do so from their accident experience. In contrast, the pattern of others' experience coefficients suggests that, while railroads do not gain from their own accident experience, their learning from each others' accident experience results in an accumulation of organizational and system-level changes that benefit all railroads; this does not occur for operating experience. Thus, in contrast with learning from own experience,

Table 1 Descriptive Statistics and Bivariate Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Accident cost per train mile	1.15	3.63																					
2 ln(age)	4.09	0.95	−0.31																				
3 ln(train miles)	16.19	2.28	−0.27	−0.29																			
4 Own accident heterogeneity	0.60	0.17	0.08	−0.23	0.50																		
5 ln(own accident costs)	15.22	2.88	0.07	−0.27	0.84	0.35																	
6 Own net income/1,000,000	0.15	0.21	0.02	−0.37	0.53	0.26	0.41																
7 ln(own capital expenditures)	11.57	1.38	0.01	−0.55	0.60	0.29	0.46	0.78															
8 ln(miles own track)	8.60	1.14	0.03	−0.59	0.57	0.25	0.47	0.69	0.86														
9 ln(miles track rights)	6.43	1.35	0.01	−0.43	0.24	0.04	0.11	0.57	0.69	0.75													
10 Left censored	0.89	0.32	0.09	0.52	−0.31	−0.13	−0.20	−0.06	−0.32	−0.31	−0.24												
11 Others' accident heterogeneity	0.74	0.03	−0.24	0.18	0.31	0.20	0.17	0.17	0.12	0.02	0.06	0.01											
12 ln(others' accident costs)	18.22	1.07	−0.34	0.07	0.61	0.41	0.56	0.06	0.05	0.01	−0.23	−0.12	0.45										
13 ln(others' capital expenditures)	14.36	0.50	−0.26	0.30	−0.08	−0.11	−0.26	0.05	0.01	−0.23	0.12	0.07	0.34	−0.04									
14 ln(others' miles track rights)	9.05	0.50	−0.19	0.28	0.04	−0.05	−0.17	0.15	0.09	0.15	0.14	−0.05	0.43	0.02	0.51								
15 ln(own operating experience)	17.93	2.24	−0.28	−0.25	0.87	0.56	0.69	0.51	0.58	0.52	0.23	−0.35	0.36	0.61	−0.02	0.11							
16 ln(own accident experience)	7.10	1.88	0.05	−0.31	0.89	0.60	0.79	0.50	0.59	0.57	0.26	−0.28	0.28	0.57	−0.10	0.21	0.90						
17 ln(others' operating experience)	24.33	1.80	−0.39	0.15	0.65	0.44	0.48	0.27	0.24	0.03	0.00	−0.04	0.56	0.64	0.44	0.56	0.73	0.59					
18 ln(others' accident experience)	8.86	0.96	−0.47	0.17	0.62	0.36	0.55	0.01	0.00	−0.03	−0.26	−0.13	0.41	0.56	−0.08	0.12	0.63	0.56	0.65				
19 Social aspiration performance > 0	163.15	305.24	0.10	−0.11	0.39	0.18	0.45	0.39	0.47	0.48	0.33	−0.05	−0.04	0.04	0.33	−0.31	0.36	0.50	−0.06	0.07			
20 Social aspiration performance < 0	−106.00	126.64	0.13	−0.47	0.17	−0.01	0.11	0.43	0.60	0.74	0.75	−0.25	−0.09	−0.41	−0.11	0.07	0.17	0.22	−0.20	−0.42	0.45		
21 Historical aspiration performance > 0	109.77	150.73	0.06	−0.37	0.39	0.23	0.42	0.11	0.32	0.44	0.26	−0.44	−0.10	0.17	−0.56	−0.49	0.37	0.50	−0.10	0.20	0.46	0.38	
22 Historical aspiration performance < 0	−17.08	53.46	0.03	0.08	−0.16	−0.04	−0.14	−0.13	−0.22	−0.16	0.13	0.09	0.06	−0.09	0.04	−0.01	−0.14	−0.13	−0.03	−0.08	−0.39	−0.14	0.16

Notes. Sample included 189 railroad-year observations; for own experience variables $\gamma = \sqrt{\text{age}}$; for others' experience variables $\gamma = \text{age}$; for historical aspiration variables $\alpha = 0.20$.

Table 2 Random-Effects GLS Models of U.S. Railroads' Accident Cost per Operating Mile

	Model 1		Model 2		Model 3 Operating experience		Model 4 Accident experience	
Variables	β	p	β	p	β	p	β	p
ln(age)	−1.056	***	−0.536	**	−0.432		−1.464	***
	(0.267)		(0.222)		(0.400)		(0.465)	
ln(train miles)	−1.893	***	−0.857	*	−0.954	*	−1.482	**
	(0.242)		(0.500)		(0.565)		(0.502)	
Own accident heterogeneity	10.773	***	0.193		−0.425		−0.608	
	(1.483)		(1.383)		(1.421)		(1.274)	
ln(own accident costs)	1.528	***	0.315	*	0.093		0.049	
	(0.144)		(0.152)		(0.164)		(0.152)	
Own net income/1,000,000	−0.319		0.184		0.000		0.000	
	(1.410)		(0.983)		(0.000)		(0.000)	
ln(own capital expenditures)	−0.202		−0.333	+	−0.144		−0.081	
	(0.324)		(0.250)		(0.246)		(0.236)	
ln(miles own track)	−1.746	***	−3.001	***	−2.478	***	−1.540	**
	(0.450)		(0.465)		(0.523)		(0.573)	
ln(miles track rights)	1.851	***	1.515	***	1.285	**	0.404	
	(0.506)		(0.413)		(0.440)		(0.447)	
Left censored	1.481	**	0.917	+	3.380	*	0.783	
	(0.652)		(0.653)		(1.598)		(0.793)	
Others' accident heterogeneity	14.201	*	−0.985		−5.585		−10.345	*
	(8.879)		(6.448)		(6.452)		(6.151)	
ln(others' accident costs)	−1.904	***	−0.586		−0.106		−0.059	
	(0.315)		(0.767)		(0.831)		(0.924)	
ln(others' capital expenditures)	−1.882	+	−1.106		−1.087		−1.470	
	(1.235)		(1.119)		(1.299)		(1.175)	
ln(others' miles track rights)	1.270		1.709	+	1.520		1.685	+
	(1.513)		(1.150)		(1.208)		(1.152)	
ln(own operating experience)			−1.291	*	−0.903		−1.256	*
			(0.622)		(0.920)		(0.601)	
ln(own accident experience)			3.384	***	3.748	***	1.124	+
			(0.473)		(0.744)		(0.872)	
ln(others' operating experience)			2.144	+	1.793		1.845	+
			(1.330)		(1.585)		(1.374)	
ln(others' accident experience)			−3.670	***	−3.278	**	−1.926	+
			(1.047)		(1.383)		(1.295)	
Social aspiration performance > 0			−0.004	***	−0.009	***	0.088	*
			(0.001)		(0.004)		(0.041)	
Social aspiration performance < 0			0.004	*	0.053	+	0.164	*
			(0.002)		(0.039)		(0.085)	
Historical aspiration performance > 0			−0.004	**	−0.027	*	−0.035	*
			(0.002)		(0.016)		(0.019)	
Historical aspiration performance < 0			0.005		0.021	+	0.116	*
			(0.005)		(0.013)		(0.064)	
SAP > 0 × ln(own experience)					0.004	*	0.011	+
					(0.002)		(0.007)	
SAP < 0 × ln(own experience)					−0.004	*	−0.008	***
					(0.002)		(0.002)	
SAP > 0 × ln(others' experience)					−0.003		−0.014	***
					(0.003)		(0.006)	
SAP < 0 × ln(others' experience)					0.015	*	0.013	*
					(0.007)		(0.007)	
HAP > 0 × ln(own experience)					0.003		0.017	*
					(0.008)		(0.009)	
HAP < 0 × ln(own experience)					−0.008	*	−0.002	
					(0.004)		(0.003)	
HAP > 0 × ln(others' experience)					−0.003		−0.020	*
					(0.006)		(0.010)	
HAP < 0 × ln(others' experience)					0.002	*	0.011	***
					(0.001)		(0.003)	
Year fixed effects	incl.		incl.		incl.		incl.	
Constant	8.760		7.246		5.223		3.808	
	(15.962)		(24.427)		(17.446)		(28.638)	
Wald chi square	440.70		1,148.78		1,402.61		1,647.54	
R^2	0.747		0.891		0.905		0.918	

Notes. $^+p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; sample included 189 railroad-year observations; for own experience variables $\gamma = \sqrt{\text{age}}$; for others' experience variables $\gamma = \text{age}$; for historical aspiration variables $\alpha = 0.20$. Standard errors are in parentheses.

railroads appear to learn how to reduce accident costs from others' accident experience but not from others' operating experience.

Railroads performing above historical accident aspirations and far above and far below social accident aspirations in the prior year exhibit lower accident costs in the current year. These findings are consistent with the idea that when a railroad's current accident performance is either far above or far below aspirations its decision makers will implement more-extensive changes to improve their accident performance, and to lower their accident costs.

Models 3 and 4 add the aspiration-performance interaction terms. In Model 3, the interactions are with operating experience; in Model 4 they are with accident experience. In the presence of the interaction terms, estimates for the main effects of experience and performance feedback are generally robust, although several change in magnitude and significance, and one changes in sign. These changes reflect the conversion of the coefficients from estimates of unconditional to conditional marginal effects in the presence of the interactions (Greene 2000, Jaccard et al. 1990).[5] With the interactions included, coefficients only indicate marginal effects when the interaction variables equal zero. For example, the coefficient for others' operating experience in Model 3 ($\beta = 1.793$), gives the marginal effect of this variable on accident costs when both social and historical aspiration performance equal zero (i.e., performance equals aspirations).

Given their conditional nature, interpreting the effect of an independent variable, X, on a dependent variable, Y, in the presence of interactions involving X and one or more conditioning variables, Z, requires taking the derivative of the entire regression equation with respect to X (Greene 2000). This eliminates terms not including X, while X and all interaction terms including X remain. More formally,

$$\frac{\partial Y}{\partial X} = \beta_x + \sum_{n=1}^{N} \beta_{xz_n} Z_n. \tag{3}$$

Using this equation, we can evaluate the marginal value of X for any values of the conditioning variables. Consider again others' operating experience in Model 3, whose positive coefficient appears to contradict the learning curve prediction. However, this coefficient only captures the marginal effect when both social and historical aspiration performances equal zero. If, instead, social and historical aspiration performance each takes its mean value, then the marginal effect of others' operating experience on accident costs is -0.650.[6] Indeed, consistent with the learning-curve predictions, the marginal effect of others' operating experience is negative over much of the range of social and historical aspiration performance. Marginal effects for the other experience variables are also generally negative, with the exception of own accident experience (Model 4), which exerts a positive marginal effect on accident costs over the entire range of social and historical aspiration performance.

Turning to the interactions themselves, estimates for 12 of 16 aspiration-performance interactions are significant in the predicted direction, although, as noted, estimates for two of the conditional main effects are not in the predicted direction. The interaction between $SAP > 0$ and own experience is significant and positive and the interaction between $SAP < 0$ and own experience is significant and negative for both operating (Model 3) and accident (Model 4) experience. Coefficients have opposite signs for the interactions of social aspiration performance (SAP) and other railroads' experience, but the interaction with $SAP > 0$ is significant only for accident experience. The interactions for own experience indicate that accident costs are reduced more by own experience the smaller the gap between performance and social aspirations. The interactions for others' experience, the opposite: accident costs are reduced more by others' experience the larger the gap between performance and social aspirations. Taken together, this pattern of interaction coefficients is consistent with the prediction that organizations emphasize exploitation of their own experience when their performance was near aspirations, and slack-driven and problem-driven exploration of others' experience when their performance was above and below aspiration, respectively. That a railroad's own accident experience is limited when $SAP > 0$ may in part account for the stronger emphasis on learning from others' accident, but not operating, experience.

The coefficients for the historical performance interactions are similar in direction, but fewer achieve significance. Only the interaction for $HAP < 0$ and others' experience is significant for both operating and accident experience. Thus, for historical aspirations, the prediction that organizations would emphasize exploratory learning from others' experience over exploitive learning from their own experience when their performance differs from aspiration levels is only supported for performance below aspirations. One possible explanation for this difference is that while $SAP > 0$ promotes slack search and learning, $HAP > 0$ leads to decision-maker complacency (e.g., Milliken and Lant 1991, Baum et al. 2005).

Again, however, interpretation of the interaction effects is complicated by the need to interpret them jointly with main effects. To aid in their interpretation, we therefore plot operating experience effects based on estimates from Model 3 in Figures 3a–3b, and do the same for accident experience based on Model 4 in Figures 4a–4b. In the figures, we vary the interactions one at a time, setting the others to their mean values following Equation (3). Experience variables are set to their sample

Figure 3 (a) Social Aspiration×Operating Experience Interactions; (b) Historical Aspiration×Operating Experience Interactions

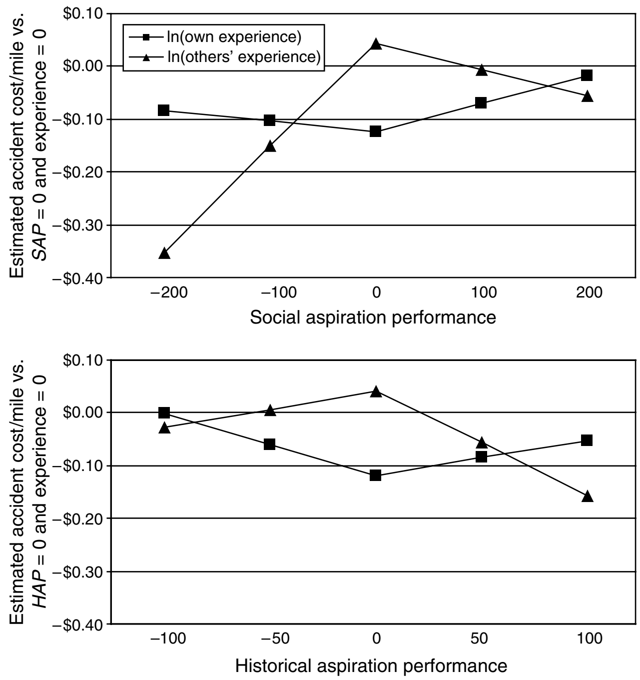
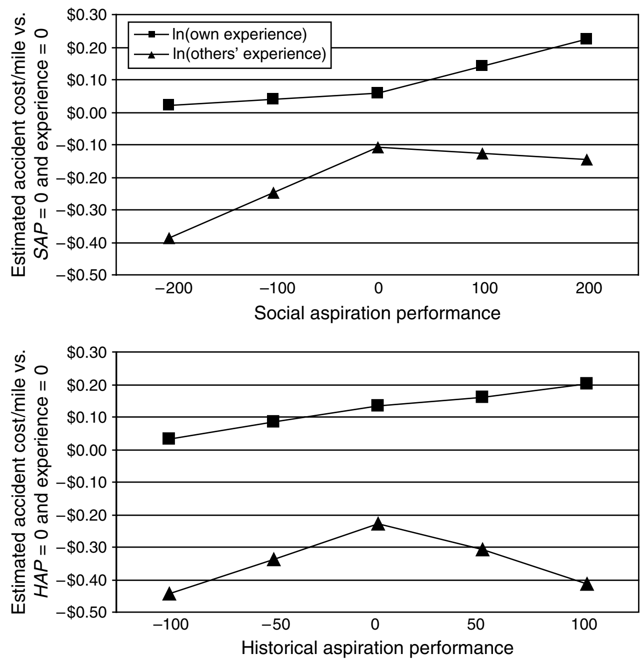


Figure 4 (a) Social Aspiration×Accident Experience Interactions; (b) Historical Aspiration×Accident Experience Interactions



means. The vertical (y) axis indicates the estimated accident cost (in 1988 dollars) relative to the case where aspiration-performance and experience are both zero, and the horizontal (x) axis indicates the aspiration performance level.

Figure 3a–3b illustrates the contrasting effect of social and historical aspiration performance gaps on the relationships between own and others' operating experience and accident costs. As the figure shows, own operating experience lowers accident costs most when accident performance is near social and historical aspirations. In contrast, other railroads' operating lowers accident costs most when performance is far from aspirations. The unexpected positive effect of other railroads' operating experience is reflected in the positive values for estimated relative accident costs as performance approaches the aspiration point (i.e., zero). Notably, however, consistent with theoretical predictions, this effect becomes negative as the gap between aspiration and performance increase, and becomes most negative for negative social aspiration performance gaps.

Figure 4a–4b shows the contrasting effects of social and historical aspiration performance gaps on the relationship between own and others' accident experience and accident costs. The figure again shows the larger effect of others' experience on accident cost reduction when accident performance is far from aspirations. The unexpected positive effect of own accident experience is reflected in the positive values for estimated relative accident costs, which are smaller when accident performance is near, rather than above, aspirations. However, the interaction of own accident experience with $SAP < 0$ weakens, but is too small to reverse the decline in accident costs as historical performance falls below aspiration, and the interaction of own accident experience with $HAP < 0$ is not significant. The positive effect of own accident experience on accident costs is thus not reinforced when performance falls below either social or historical performance aspirations.

Taken together, Figures 3a–3b and 4a–4b corroborate the conclusion that railroads' attention shifts from learning from their own accident and operating experience, to learning from others' accident and operating experience as performance deviates from aspiration levels. The figures also illustrate two further notable points: One is that the interaction effects are more pronounced for others' experience than for own experience. This is consistent with the idea that performance away from aspirations is associated with more-extensive changes to reduce accident costs, and that in order to generate such changes, organizations look beyond their own boundaries to others' experiences as a source of learning. The other is that the learning curve for railroads' accident costs is driven more by cumulative accident experience than by cumulative operating experience. Thus, experience with accidents is more germane than experience with successful operations to accident cost reduction, highlighting the importance of identifying the type(s) of experience likely to inform particular learning efforts to avoid concluding erroneously that learning is not occurring.

Discussion

Although the estimates are generally consistent with aspiration-performance feedback predictions, and offer considerable support for the predicted pattern of interactions between aspiration performance, and own and others' experience, two of the experience main effects remain puzzling, and warrant further discussion: One is the effect of others' operating experience, which has a positive effect on accident costs when performance is near aspirations, and the other is the effect of own accident experience, which positively influences accident costs regardless of aspiration-performance levels.

The pattern of others' experience coefficients suggests that while railroads learn how to reduce accident costs from others' accident experience, others' operating experience sometimes increases accident costs. One possible explanation for this result is that coefficients for others' operating experience spuriously capture the greater likelihood of encounters with trains operated by different railroads, and thus positively affect accident costs. For this reason, we included each railroad's miles of track rights and other railroads' miles of track rights in all models to control for the extent to which railroads operate on each other's tracks. Coefficients for these two variables are both positive, but neither is consistently significant. Nevertheless, with these controls removed the magnitude of the others' operating experience coefficient increases, on average, roughly 40% across the models. This attenuation is consistent with the idea that the positive effect of others' operating experience, at least in part, spuriously captures railroads' encounters on each others' tracks.

The pattern of own experience coefficients suggests that, while railroads learn how to reduce accident costs from their cumulative operating experience, they do not do so from their accident experience. While it is understandable that lessons from railroads' operating experience can indirectly lower accident costs by increasing the success of their future operations, why accident experience does not do so more directly is not so understandable. One explanation for this contrary result may be that the history-dependent and incremental nature of organizational routines and learning (Cyert and March 1963, Nelson and Winter 1982) leads some railroads, despite ample accident experience from which they can learn to be persistently accident prone. This accident proneness might also be a function of factors beyond the control of individual railroads, such as characteristics of the terrain and climate where they operate.

A second explanation may be that railroads' accidents are relatively infrequent; involve complex systems and technologies that can result in accidents that are difficult to understand or control; involve multiple interested parties (e.g., railroads, insurers, customers, authorities, equipment manufacturers, and the public), each with its own incentives to interpret and frame accident causes in particular ways. All of these conditions can inhibit both individual and collective learning. As a result, to learn effectively railroads, similar to HROs, must explore meaningful analogues that aid in their learning from others' accidents. Thus, while contrary to predictions of the learning-curve model, our findings are consistent with the Weick et al. (1999) observation that other organizations' failures are vital to learning, because individual organizations that lack sufficient experience with failure to learn from it turn to others' failures for clues about the causes of their own problems and to learn what not to do.

Our findings are also consistent with research pointing to technical, structural and psychological factors that impede learning from own failures (e.g., Finkelstein 2003, Baumard and Starbuck 2005, Cannon and Edmondson 2005, Starbuck and Farjoun 2005, Rerup 2006). Technical hurdles include a lack of ability to systematically draw inferences from experiences with complex systems or technologies, which can result in erroneous conclusions that inhibit learning. Structural hurdles include policies and procedures that reward success and penalize failure, creating disincentives for management and employees to identify and analyze failures (Argyris 1990). Psychological hurdles originate in our deep aversion to acknowledging failure, which leads us to tend to attribute our successes to internal causes (e.g., our own actions) and failures to external causes (e.g., others' actions or environmental conditions) beyond our control (Weiner 1971, 1985). These psychological proclivities may be incompatible with acknowledgement of failure, increasing the likelihood that attempts to learn from failure will degenerate into exercises in finger pointing or name calling, straining relationships and creating ill feelings rather than learning (Cannon and Edmondson 2005).

Conclusion

Given the centrality to learning theory of the idea that organizations learn from their own and each other's experience and make changes conditional on their performance, it is puzzling that we do not know how organizations' experiential and vicarious learning is influenced by performance feedback. In this paper, we take a step toward integrating these perspectives by connecting aspiration-performance and learning-curve models. Although past research has demonstrated that organizations learn experientially and vicariously from own and others' successes and failures, no study had yet explored the relationship between learning from experience and aspiration-performance feedback (but see Haleblian et al. 2006). We theorized and modeled U.S. freight railroads' accident costs as a learning curve driven by experiential and vicarious learning from their own and other railroads' operating and accident experience.

Our theoretical focus was on how a railroad's rates of learning from their own and each others' experience are conditioned by aspiration-performance feedback. Our findings reveal a multifaceted accident learning process influenced by performance contingencies that can focus railroads' learning toward or away from their own and each others' experience.

Results were broadly consistent with several well-established learning theory ideas, but posed some challenges to them, as well. We found evidence of problem- and slack-driven search, with railroads performing above or below historical and social accident aspirations tending to experience lower accident costs in the following year. Some caution must be exercised in interpreting our search findings, however, since, like most other performance feedback studies, we do not observe railroads' search behavior directly.

Our analysis also revealed experiential and vicarious learning curve effects, with U.S. freight railroads' accident costs declining with increases in their own operating experience and other railroads' accident experience. But we also found evidence, contrary to learning-curve predictions, that railroads' accident costs tended to increase with others' operating experience and their own accident experience. We attributed the first of these contrary results, in part, to railroads' encounters with each other on the other's tracks. For the second, we considered several explanations—history-dependent organizational routines and learning; lack of sufficient experience with complex accidents from which to learn; and technical, structural, and psychological impediments to learning from failure. These interpretations of our findings suggest that learning from successful and failed operations may be fundamentally different.

These results for accident cost reduction are significant to the learning-curve literature, which has focused primarily on productivity, and which has only recently begun to address accident and error reduction (Haunschild and Sullivan 2002, Haunschild and Rhee 2004). Error and accident reduction has important practical implications for organizations, the economy, and society (Perrow 1984). The analysis also advances learning-curve research by simultaneously modeling learning from successful and failed operations. While traditional learning curves for productivity consider the costs of failures (e.g., Lester and McCabe 1993) in the form of rework or downtime costs, for example, those traditional learning curves do not consider the role of experience with such failures for learning curves. Given the central role of failure in understanding the causes of success (e.g., Popper 1959, March 1991, Petroski 1994), we think future studies in the learning-curve tradition, whether focused on improving productivity or on reducing errors, would benefit from explicit specification of failure experience; and that the possibility that learning from successes and failures are fundamentally different processes should be contemplated theoretically.

In addition to evidence of learning-curve and aspiration-performance feedback effects on accident cost reduction, the results offered novel insights into the hypothesized relationship between these two learning models and, specifically, the extent to which railroads' learning from their own and others' operating and accident experience depends on their performance. As hypothesized, we found that others' accident and operating experience tended to have stronger effects on accident cost reduction as a railroad's performance either rose farther above or fell farther below its social and historical aspiration levels; we also found that own accident and operating experience tended to have stronger effects on accident cost reduction when performance was near aspiration levels. This effect of performance feedback on patterns of experiential and vicarious learning, which speaks directly to patterns of managerial attention and the balance between exploration and exploitation under different performance conditions, has the potential to increase our understanding of a range of organizational learning phenomena. Conventional wisdom is that poor performance can disrupt the status quo and trigger new learning; while research tends to support that wisdom, the relationship between performance feedback and change—not learning—is the main focus of this research (for reviews, see Greve 2003, Milliken and Lant 1991). We show that when railroads' performance is far from social aspirations, others' accident and operating experience has a stronger effect on accident cost reduction, while railroads' own experience contributes more when their performance is near aspirations. Reinforcing conventional wisdom, such a shift in patterns of attention seems likely to trigger nonlocal search and exploratory learning that may be essential to processes of organizational adaptation.

Our findings also have implications for the closely related qualitative literature on learning from accidents by HROs. Studies of HROs typically begin with the occurrence of a major accident at a particular organization. Under such conditions, accident performance is below aspirations, conditions under which our theoretical argument suggests that organizations are likely to emphasize exploratory learning from others' experience, which is indeed the typical finding in these studies (Weick et al. 1999). In contrast, we studied multiple organizations' accident histories over an extended period of time, which permitted us to demonstrate empirically the shifting attention between exploration and exploitation as accident performance changed relative to aspirations. Thus, our empirical findings bolster insights from investigations of HROs, supporting the Weick et al. (1999) suggestion that the adaptive characteristics exhibited by effective HROs might usefully be made more central to research on organizational learning. At the same time, however, our analysis, which offers insight into the balance between exploration and exploitation under different performance conditions, identifies a critical contingency affecting the generalizability of the HRO findings to the mainstream literature on organizational learning in general, and learning from failure in particular.

While our study reveals some new connections between experiential and performance-feedback learning models, many questions remain open. Our findings suggest a number of directions for future research, some stemming directly from limitations of this study. One is that, like most studies in the learning curve and performance feedback traditions, our data do not permit us to examine the underlying learning processes directly. We present ideas and examples of how experience and performance feedback can affect accident costs, but our empirical models do not examine the intermediate processes by which problem- and slack-driven search affect learning from operating and accident experience, nor do we examine the process through which operating or accident experience reduces accident costs. Fortunately, the ways in which decision makers do (or do not) learn from their own and others' experience are increasingly well understood (e.g., Darr et al. 1995, Darr and Kurtzberg 2000, Lapré et al. 2000), and our analysis is meant to point to their collective importance, and not to determine their relative importance. Future research investigating processes underlying these effects would be valuable. For example, the details of railroads' interpretations of and responses to their own and other railroads' accidents could be followed and comparisons made between railroads performing near to and far from aspirations.

It is also possible that features unique to the railroad industry (e.g., FRA and NTSB actions) promote learning from accidents, or that the visibility and consequences of accidents motivate their reduction, limiting the generalizability of our findings. Mitigating this concern is the increasing scope of empirical settings (banks, nursing homes, hotels, airlines, or tire producers) and types of failure (organizational, strategic, operational, or product) examined in the growing stream of research examining organizations' learning from failure. Nevertheless, future research in a broader set of industries and across a wider range of failures is necessary. A related point is that, while it is increasingly clear that organizations learn from both success and failure, it is unclear whether organizations learn more, or more effectively, from success or from failure. Our findings suggest that the answer to this question may depend on whether the learning is focused on productivity or other improvements on the one hand, or on accident cost or error reduction on the other. We also wonder what balance of success and failure is optimal for organizational learning. While some degree of failure is necessary to learn the reasons for success, what failure rate produces the most rapid learning of reasons for success? How does this balance differ for productivity improvement and accident and error reduction?

In addition to the relative benefits of learning from success and failure, our study raises questions about the relative magnitudes of social and historical aspiration effects: for the railroads in our sample, performance relative to social aspirations had a stronger influence than historical performance on patterns of experiential learning. We wonder, more generally, about the relative influence of historical and social performance feedback. Is it because the performance outcome we examined—accident cost reduction—is externally scrutinized that social performance influences behavior more strongly than it influences self comparisons? Or is it because features unique to the railroad industry (e.g., actions of the FRA and NTSB) promote social comparison? Identifying factors influencing the relative strengths of social and historical aspiration effects on learning curves is an open research area.

Several measurement issues are also apparent. Our measure of accident experience treats all accidents as equal, a useful starting approximation. Accidents vary greatly, however, in cause and consequence, and it seems likely that more will be learned from some accidents than from others. For example, more-consequential accidents may foster greater learning because of their visibility than do relatively inconsequential accidents. This suggests the need for more fine-grained data that permit measures that weight individual accidents according to the magnitude of their consequences (e.g., costs, and people killed or injured), as well as their interpretability (Kim and Miner 2006) and the number of parties involved. Haunschild and Sullivan (2002) also show that accidents with more heterogeneous causes can produce more learning. Although we did not replicate this finding, data limitations forced us to measure the heterogeneity of accident causes at the organization-year, not accident, level.

Also open is the question of social reference groups. We defined railroads' comparison group implicitly based on class (i.e., size or scale of operations), which is consistent with cognitive categorization research showing that size similarity is a key variable influencing managers' construction of peer groups that shape their strategic and competitive behavior (e.g., Lant and Baum 1995, Porac et al. 1995, Reger and Huff 1993). A related point is the importance of identifying the type or types of experience and performance metrics likely to inform and trigger particular learning efforts in the model specification process to avoid concluding erroneously that learning is not occurring. Future research specifying others' experience and social aspirations with more attention to reference group definition and experience and aspiration performance variables germane to the learning focus may be instrumental to increasing the precision and realism of performance-feedback models (Baum et al. 2005).

We know a good deal about experiential learning and performance-feedback processes, but we know too little about the relationship between these models of organizational learning. Our analysis indicates that, in the context of accident cost reduction, performance-feedback models provide the conditions under which organizations will tend to learn more from their own than from other organizations' experience: organizational learning curves reduce accident costs more when performance is near aspirations; interorganizational learning curves do so when performance is far from them. We believe this conditioning may be essential to processes of organizational adaptation, and hope our analysis provides groundwork for those interested in constructing more-integrated models of organizational learning and change.

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Endnotes
[1]These include accident-related costs incurred for containment, cleanup, cause investigation, evacuation, equipment repair and replacement, and legal liabilities in case of death or injury. For example, consider a 42-car Norfolk Southern freight train carrying chlorine gas that collided with a train parked at a crossing in Columbia, SC, killing nine people and sickening more than 250 on January 8, 2005. Direct costs associated with this accident included investigation and containment conducted by highly trained workers in protective suits and oxygen tanks, 40 tons of crushed lime to neutralize the chlorine, removal of damaged cars, repair of track and equipment, hotel rooms for one week and \$100 gift cards or checks for 5,400 displaced residents. Direct costs do not include, i.e., insurance premium increases (railroads often self-insure due to high costs of third-party insurance), or revenues lost due to service disruption or damage to reputation (Luczak 2006).

[2]To determine the discount rate, we estimated operating and accident experience variables for four values of γ: 1, or no depreciation, $\gamma =$ experience age, a less-than-linear depreciation with age, $\gamma =$ experience age, a linear depreciation, and $\gamma =$ experience age^2, a faster-than-linear depreciation (Ingram and Baum 1997). Estimates for own operating and accident experience using $\gamma =$ experience age and estimates for others' operating and accident experience with $\gamma =$ experience age were more efficient, yielding higher coefficient t-statistics and model R^2s. This indicates that the value of others' experience for accident cost reduction depreciates approximately linearly with the age of the experience, while the value of own experience depreciates more slowly. In the analysis reported, we use estimates based on these specifications.

[3]To determine an appropriate value for the updating parameter, following Greve (1998), we constructed and estimated aspiration levels for five values of α: 0.05, 0.10, 0.20, 0.25, and 0.30. Estimates based on $\alpha = 0.20$ were more efficient, yielding higher coefficient t-statistics and model R^2s. In the analysis reported, we use estimates based on this specification.

[4]We compute operating and accident experience and historical aspirations variables for 1981 using statistics for the 1975 to 1980 period to reduce the impact of left censoring on these variables.

[5]It is also possible that a decrease in significance for main effects is multicollinearity. Inspection of main effects' standard errors for inflation yields no evidence that this is the case, however. That said, we are not concerned with the significance of individual parameters for main and interaction effects, but rather with their joint significance (Jaccard et al. 1990), which we confirmed for each experience variable and its aspiration-performance interactions: *Own operating experience*: $\chi^2(5df) = 11.31$ ($p < 0.05$); *Others' operating experience*: $\chi^2(5df) = 10.18$ ($p < 0.10$); *Own accident experience*: $\chi^2(5df) = 26.72$ ($p < 0.01$); *Others' accident experience*: $\chi^2(5df) = 52.05$ ($p < 0.001$).

[6]At mean social and historical aspirations, $\partial X/\partial Y = 1.793 + (-0.003 \times 163.15) + (0.015 \times -106.00) + (-0.003 \times 109.77) + (0.002 \times -17.08) = -0.650$.

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