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Organizational Learning from Extreme Performance Experience: The Impact of Success and Recovery Experience

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This paper argues that two different types of a firm's own extreme performance experiences—success and recovery—and their interactions can generate survival-enhancing learning. Although these types of experience often represent valuable sources of useful learning, several important learning challenges arise when a firm has extremely limited prior experience of the same type. Thus, we theorize that a certain threshold of a given type of experience is required before each type of experience becomes valuable, with low levels of experience harming the organization. Furthermore, we propose that success and recovery experience will interact to enhance each other's value. These conditions can help overcome learning challenges such as superstitious learning or learning from small samples. We investigate our ideas using a sample of the U.S. commercial banks founded between 1984 and 1998. Our results indicate that both success and recovery experience of a firm generate survival-enhancing learning, but only after a certain level of experience is reached. Furthermore, success and recovery experience enhance each other's learning value, consistent with the theories that emphasize the importance of richer and contrasting experience in providing useful knowledge. Our framework advances organizational learning theory by presenting a contingent model of the impact of success and recovery experience and their interaction.

Key words: organizational learning; extreme performance experience; success and recovery experience; learning from failure
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> It ain't what you don't know that gets you into trouble. It's what you know for sure that just ain't so. (Mark Twain)

Learning from unusual performance outcomes such as success or failure experiences has increasingly drawn scholarly attention (e.g., Baum and Dahlin 2007, Greve 2003b, Miner et al. 1999, Sitkin 1992). This emerging literature has significantly expanded our horizons in understanding how organizations learn from prior experience above and beyond the conventional operating experience. The studies on this topic imply that success and failure experiences have distinct characteristics and features that set them apart from other types of experience. However, this work often assumes a traditional learning-curve perspective, which generally predicts a monotonic positive relationship between the amount of experience and performance outcomes (Argote and Epple 1990, Audia et al. 2000, Lant and Montgomery 1987, Thornhill and Amit 2003). In this paper, we explicitly consider the specific features of success and failure and propose that this assumption does not necessarily apply to learning from success and failure experience. We advance a framework in which the impact of success- and failure-related experience will depend upon two key factors: the level of experience and the presence of the other type of experience.

We first present theories about learning from two types of extreme performance experience: success and recovery. We define *success experience* as a firm's cumulative history of periods of exceptionally strong performance. *Recovery experience* is a type of failure experience defined as occurring when a firm experiences extremely poor performance but later overcomes it. We argue that, although both success and recovery experience have great potential for generating useful learning, they can also produce harmful learning outcomes in the absence of sufficient prior experience of the same type. We then propose that such harmful learning outcomes can be overcome through the accumulation of more experience of the same type.

We predict this pattern based on theory that has long emphasized that past experience is not always a good teacher and may lead to inaccurate models of the world, inappropriate actions, and dysfunctional learning outcomes (Levinthal and March 1993, March 1991, Miner et al. 2001). Our framework highlights the concept that extreme performance outcomes such as a firm's own success and recovery experience are inherently difficult to interpret and that they can even cause dangerous cognitive biases, attribution errors, and superstitious learning until some threshold level of such experience is reached (March et al. 1991). Without enough experience to correct such biases, the dangers of inferential error may far outweigh the potential benefits of learning from success or recovery (Denrell et al. 2004, March et al. 1991). In addition, the high salience of extreme performance outcomes also increases the chances that they will have a major impact on firm behavior even when the lessons drawn from such experiences are inaccurate (Haunschild and Miner 1997). Thus, instead of assuming that learning from success and recovery experience will necessarily be adaptive, we theorize that it will negatively affect a firm's performance when the firm has only limited experience of the same type, but that it can generate positive outcomes at higher levels of experience. The additional experience help firms draw more accurate inferences and choose actions that are more likely to have value.

We also propose that success and recovery experiences will moderate the impacts of each other. The *combination* of the two types of experience offers a richer range of linked prior actions and outcomes, as well as contrasts between periods or episodes (Morris and Moore 2000), which makes it possible to improve inferential learning. The combined experience also generates a broader range of potential actions that the firm can take (Haunschild and Sullivan 2002). Thus, the combination of success and recovery experience should enhance any positive impact they offer. Our emphasis on the combination of different experience types helps move the learning literature forward because prior studies have tended to focus on only one type of experience at a time. Prior work has provided evidence that firms can learn from different types of experience, such as failure in naming strategy (Chuang and Baum 2003), product recall (Haunschild and Rhee 2004), or improvisational activities (Miner et al. 2001), but it has not typically examined combined experience effects. Our study offers a distinct perspective in which two experience types associated with opposite performance outcomes will enhance each other's value.

We investigate our hypotheses using a sample of all U.S. commercial banks founded between 1984 and 1998. In testing our ideas, we follow the research tradition of organizational learning literature that links organizational experience with particular learning outcomes. Specifically, we build on the *survival-enhancing learning* framework put forth by Baum and Ingram (1998), which is defined as a type of learning that occurs when experience decreases an organization's risk of failure. We examine whether recovery and success experience and their interaction produce survival-enhancing learning as our theory predicts. Survival is a particularly appropriate learning outcome for this study context because enhancing the prospect of survival is often a new firm's most critical goal.

Our findings provide strong support for the notion that both recovery and success experience can generate survival-enhancing learning. At the same time, our findings also show that recovery and success experiences enhance the survival chances of banks only after a certain level of experience has been acquired, and that they interact with each other to enhance the value of such learning. This provides evidence for our theory that firms face considerable learning challenges in drawing fruitful lessons when they have limited extreme performance experience, but that additional experience can help them overcome these challenges.

This paper's primary contributions to the literature are fourfold. First, we move away from generic experience and instead probe the implications of two important types of organizational experience: success and recovery. Thus, this study advances our understanding of organizational experience above and beyond the focus on cumulative operating experience, which tells us little about the specific nature of a firm's past experience.[1] Second, we provide evidence that when prior experience of the same type is very low or absent, success and recovery experience can generate harmful learning outcomes, but that additional experience can reverse this effect. This finding advances the learning literature by underscoring prior theories on learning challenges to develop a conditional model of the impact of different levels of extreme performance outcome experience. Third, our findings support the theoretical prediction that the combination of different types of experience can enhance useful learning. This study represents an early study that compares and examines the interaction of multiple types of experience, and to the best of our knowledge, this study is the first effort to explore the combined effects of success- and failure-related experience. Finally, we advance the emerging literature on organizational entrepreneurial learning by explicating the impact of organization-level success and recovery experiences in new firms.

Theory and Hypotheses

Learning from a Firm's Own Success Experience

In developing our hypothesis on the impact of success experience, we first briefly discuss existing theory, which often proposes that it will have a positive learning impact. We then focus on why success experience can produce counterproductive learning in the presence of very little prior success experience, and move onto why the addition of more success experience should reverse this negative effect.

The behavioral theory of the firm has long recognized that organizational reactions to success and failure represent an important potential mechanism through which organizational learning occurs (Cyert and March 1992). Boundedly rational managers often divide prior performance outcomes into dichotomous judgment of success and failure, and then modify their behavior based on the categorization of prior performance (Cyert and March 1992, Greve 2003b, March and Simon 1958). Thus, both success and failure can promote useful learning processes.

In particular, success can serve as an indicator that current strategies or actions are effective in the current environment, and it can facilitate organizations in retaining strategies and routines that contributed to their success (Audia et al. 2000, Greve 1998, Kraatz 1998, Schwab 2007). This can reduce wasteful organizational search efforts and improve efficiency and performance (Greve 2003a, Levinthal and March 1993). Furthermore, because success experience is highly salient, it draws attention within the organization and inspires confidence in ongoing learning activities (Schwab and Miner 2008). This in turn can point to promising areas for further search (Ocasio 1997, Simon 1997) and stimulate slack search, which can lead to novel and useful knowledge and capabilities (Cyert and March 1992). These potential benefits of success experience are not only well documented in the literature but also quite intuitive. However, learning from success is also subject to behavioral and cognitive biases and errors (Sitkin 1992, Tversky and Kahneman 1974), which are especially problematic when firms have only limited prior success experience. Thus, we propose that the potential values of success experience may not lead to useful learning until sufficient levels of success experience have been reached to overcome these dangers.

Danger of Limited Success Experience. When a firm tries to learn from a very few prior success events, it can be led into several learning processes that can generate harmful rather than useful outcomes. Success is often a noisy signal of the effectiveness of prior actions; e.g., success can be a result of simple luck or persistent use of a high-risk strategy (Denrell 2005). Thus, it is not easy to establish an accurate causal relationship between a success and its antecedents (Denrell et al. 2004, Minsky 2006). Nonetheless, managers tend to make an implicit assumption that success is a result of the effectiveness of their prior actions even when they do not have a clear understanding of what caused the success (Miller and Ross 1975, Van de Ven and Polley 1992, Weiner 1986).

In addition, managers tend to assign unwarranted weight to success experience and to downplay signs of poor performance in other parts of the organization because they want to portray themselves as successful managers (Audia et al. 2000, Kunda 1999). This can lead to an oversampling of success experience that can cause errors in inference (Denrell 2003, Hayward 2002). This tendency to place more credence on success experience than its true value warrants presents a danger of superstitious learning. This form of learning occurs when firms take actions based on a mistaken identification of specific routines and causal processes that contributed to experienced success and/or fail to distribute proper credits to each routine's contribution to success (Denrell et al. 2004, Levinthal and March 1993).

These dangers can occur when a firm tries to learn from any level of success experience, but the potential biases and errors of interpreting success are most likely to occur among managers of firms with *limited prior* success experience. The learning literature suggests that learning from limited experience presents significant learning challenges because firms must rely on a small number of events in inferring what actions generated which outcomes (March et al. 1991). The small sample size increases the margin of error and the potential biases in interpreting prior success events, thus raising the probability that firms will derive incorrect conclusions from the experience and/or engage in superstitious learning (Denrell 2003).

Specifically, limited prior success experience can lead firms to inaccurately attribute their success to routines or strategies that, in truth, did very little to produce the success. The incorrect attributions arising from insufficient information will lead them to adopt suboptimal, irrelevant, or even harmful actions and routines, consequently undermining their viability (Kim and Finkelstein 2009, Levitt and March 1988). Investing in incorrect routines is especially costly to firms constrained by limited resources and operating funds (Baker and Nelson 2005). Consistent with these arguments, Haleblian and Finkelstein (1999) found a U-shaped relationship between acquisition experience and acquisition performance; i.e., low levels of acquisition experience negatively influenced performance until a firm accumulated a certain level of acquisition experience. They attributed the negative impact of acquisition experience to firms' inappropriate generalizations from insufficient experience in the specific domain of acquisitions. We similarly argue that limited success experience will lead firms to overgeneralize the value of actions taken before the success without a careful analysis of causal factors, a learning process that can harm the firm as a whole (March 1999b). In sum, firms with limited success experience can make mistakes in identifying actions that should be repeated (trial and error learning) and/or in constructing accurate cognitive maps of the causal world in which they operate (inferential learning).

The danger of superstitious learning is exacerbated by the overconfidence that early success instills in the organization and its managers and stakeholders (Cooper et al.

1988). Success increases confidence in the prior actions (Audia et al. 2000, Sitkin 1992), and encourages interpretation that is consistent with prior assumptions rather than being useful for learning from current experience (Fiske and Taylor 1991). Thus, managers often infer from their initial success that their firm is more capable than it really is, which can lead to ill-informed strategies as well as inattention to threats. Encouraged by initial success, they may also act more boldly and take more ill-considered risk, increasing the risk of failure of their firm. In short, managers' overconfidence due to a few early strong successes can produce quick actions driven by superstitious learning, thus exposing their firms to a high risk of failure. Comments by a senior manager at a small California ethnic bank that started its operation in the late 1990s illustrate this danger:[2]

> When we first started, much of our business came from new immigrants [from a foreign country], mostly small business loans and personal credits. Our operating results during the first couple of years exceeded everybody's expectations. So, we continued to focus on that customer group until recently. But, in retrospect, it was a pretty risky strategy because they are a high-risk group. This strategy also began to limit our growth. We are not doing it any longer.

Overall, the combination of superstitious learning, overconfidence, and overestimation of firm capabilities derived from limited success experience is highly likely to generate harmful learning outcomes.

Positive Learning Value from Additional Success Experience. We theorize that additional success experience will mitigate the negative effects of initial success experiences. As firms experience *new* and *separate* episodes of success that were achieved in different areas and contexts, they gain new information that can help them avoid the behavioral and cognitive biases associated with the initial limited experience. Stated differently, a greater amount of success experience allows firms to benefit from a richer array of actions and outcomes, and to contrast aspects of each phase with one another. This, in turn, makes it possible for them to develop a more comprehensive and valid causal map and richer repertoire of actions (March et al. 1991). Additional success experience allows firms to improve their chances of correctly identifying the routines and strategies that are responsible for their prior success and repeat actions that were truly effective. Firms can develop a deeper understanding by analyzing the patterns in the different success periods and the consequences of prior success-driven learning. Thus, higher levels of success experience can reduce learning biases and errors, and increase the chance of harvesting value from prior successes (Levinthal and March 1993, March et al. 1991).

The valid identification of actual causes of success experiences can also permit more efficient use of resources. If a firm identifies routines that truly "work," it can focus more on perfecting those than on searching for potential alternatives (March 1991). Thus, it will become more proficient in performing activities that genuinely produce value, which in turn can improve its operating efficiency and performance. This can be beneficial for three reasons. First, it allows the firm to save resources that would be otherwise spent on costly, random search. Second, it can help the firm focus on key operational issues that have direct bearing on firm growth and survival. Third, it can decrease the level of risk to which a firm is exposed by limiting unfruitful exploration (Greve 1998).

Behavioral theories have traditionally argued that success can slow down overall organizational search and experimentation if most search is problem-driven (Cyert and March 1992). Success does not completely eliminate organizational search activities, however. Repeated success can allow firms to generate higher profits and stronger cash flow, which can help them accumulate slack resources that in turn spur slack search (Baum et al. 2005, Cyert and March 1992). Slack search can help firms incrementally improve upon existing routines without disrupting core operations or negatively influencing performance (Greve 2003b, Levinthal and March 1993). In addition, slack search can generate innovations that enhance the firm's adaptive capabilities (Greve 2003a). Repeated success, then, can encourage managers and entrepreneurs to increase some search activities that improve existing routines and to explore new areas, and create a richer set of options for action.

In sum, we expect that a limited number of early successes will be harmful to a firm's performance and that the value of success experience will be realized only after new firms experience a threshold level of successes. This implies an inverse U-shaped relationship between success experience and organizational failure, leading to the following hypothesis:

HYPOTHESIS 1. *There will be an* inverted U-shaped *relationship between the amount of success experience of a focal bank and the failure rate of the bank.*

Learning from a Firm's Own Recovery Experience

Research on organizational learning has suggested that firms can learn fruitfully from their own and others' failure experiences (Chuang and Baum 2003, Miner et al. 1999). Failure-related constructs include many events above and beyond the traditional concepts of survival and dissolution. Consistent with this, learning scholars have recently begun to explore learning from different failure-related experiences such as product recall (Haunschild and Rhee 2004) and industry-level near-failure (Kim and Miner 2007). Our study advances this emerging literature by theorizing about how firms learn from *their own recovery experience*. We define this type of failure experience as occurring when a firm faces imminent failure due to a critical performance decline but later substantially improves its performance above an acceptable level (Kim and Miner 2007).

By definition, recovery experience involves periods of extremely low performance followed by strong performance improvement, which offer useful contrasts to support fruitful learning. As firms overcome life-threatening situations, they may abandon or revise ineffective routines (Wiseman and Bromiley 1996), implement new strategies (Barr et al. 1992), or try to develop new capabilities (Ocasio 1995). Corporate renewals or turnarounds can represent recovery experiences, for example. The lessons drawn from actions taken to escape from failure can allow firms to respond more effectively to similar problems they may encounter in the future, or help them avoid experiencing another problem altogether (Mezias and Glynn 1993). Indeed, recovery experience may have an even higher learning value than success by offering pre–post contrasts and apparent working solutions to prior threats, as well by engendering strong reactions of organizational members (Kim and Miner 2007). However, like success experience, recovery experience is subject to several problems that may generate negative, nonadaptive learning outcomes when firms do not have sufficient recovery experience.

Dangers of Limited Recovery Experience. Despite the intuitive appeal of recovery experience as a potential source of useful learning, limited recovery experience can produce counterproductive learning outcomes. The potential dangers of learning from limited recovery experience mirror many of the dangers of learning from limited success experience, but there are also some dangers specific to learning from recovery. As we discussed in the case of success experience, generalizing from limited experience can lead to superstitious learning (Huber 1991, Levitt and March 1988). Paradoxically, this danger may be exacerbated by the very characteristics that make recovery experience an attractive source of learning.

When faced with a problem, boundedly rational managers tend to adopt a preexisting solution that they used in the past rather than develop a new solution (Levitt and March 1988). This makes recovery experience particularly attractive because recovery experience provides a working solution to a threat that can be potentially used again when a similar problem should arise (Kim and Miner 2007). If firms take specific actions to deal with threats, they will often see them as *working* solutions to the perceived threats, even if these actions did not cause the recovery. Thus, managers with initial recovery experiences are tempted to reuse the lessons drawn from the experience (Kunda 1999). They will actively seek to implement the same actions when they face problems in the future, hoping to replicate similar outcomes (Levinthal and Rerup 2006). However, because individual problems often require unique solutions, blindly applying the solutions learned from a small sample of prior recovery experience without a clear grasp of the problem at hand can produce harmful learning outcomes (March et al. 1991). Misplaced confidence in these apparent solutions can also take attention away from genuine threats at hand (Ocasio 1997). Thus, although recovery experience seems to provide working solutions to serious managerial problems, this very feature can increase the chances of harmful learning outcomes in the presence of little prior recovery experience.

Furthermore, severe performance distress is likely to elicit much attention from the managers within a firm because it can escalate into an even more undesirable consequence—firm failure. Successfully fending off a distress situation draws even more attention from managers who enthusiastically seek opportunities to share their tales of victory, in contrast to stigmatizing outcomes such as bankruptcy (Miner et al. 1999). This combination enhances the emotional appeal of recovery experience, which in turn encourages managers to accept their experience at its face value and take action based on its seemingly apparent value even if their limited experience does not allow them to draw valid lessons.

Positive Learning Value from Additional Recovery Experience. As with success experience, the impact of the errors and biases associated with learning from recovery experience will diminish as firms gain recovery experience sufficient to allow them to correct these mistakes. The longitudinal comparison of multiple recovery events can engender useful learning by helping managers establish a more well-informed understanding of causal relationships between variables that may have contributed to their experience. An isolated or limited level of recovery experience may be simply dismissed as an abnormal event. However, additional recovery episodes can increase the chances that a firm will anticipate potential threats, more accurately evaluate the risks of future problems, and act on more realistic assessments of the threats of future problems, consequently lowering the risk of failure (March et al. 1991).

A record of failure-related experiences not only makes it more likely that the firm can validate apparent solutions to prior challenges, but also allows the firm to accumulate a repertoire of strategies that are truly effective in fending off certain types of distress (Sitkin 1992). These tested actions are particularly valuable because they arise from a firm's own experience, are relevant to the context in which the firm operates, and are closely aligned with the firm's resources and capabilities (Levitt and March 1988). In sum, repeated recovery episodes can provide a toolkit of tested working solutions that a firm can deploy when similar problems arise, but also provide sufficient context to increase the chances that the solutions will be relevant and inferences from recoveries will be appropriate. This notion was implied by a senior manager from a U.S. subsidiary of a foreign bank:[3]

> We are in the business of taking risks, so bad things are bound to happen. Bad loan accounts and miscalculated investments are facts of life for banks. We cannot possibly come up with a new solution every time we have a problem. It is impractical and dangerous because we don't know whether it will work. So, it is extremely important to keep track of our past problems and how we took care of them. We've created action templates from our experience, and we expect managers to follow them when a similar problem arises.

In sum, these theories imply that recovery experience will produce harmful learning outcomes for firms when they have a small amount of recovery experience, but that once sufficient levels are reached, recovery experience will have a positive learning impact. This leads us to our second hypothesis:

HYPOTHESIS 2. *There will be an* inverted U-shaped *relationship between the amount of recovery experience of a focal bank and the failure rate of the bank.*

The Interaction Between a Firm's Own Success and Recovery Experience

Firms acquire different types of experience throughout their histories, and each type of experience provides opportunities for both useful and destructive learning outcomes, conditioned on the level of the same type of experience. Our final hypothesis proposes another condition that should shape the learning potential for success and failure experience: the joint impact of the two types of experience on each other. To our knowledge, the interaction between different organizational *experience types* has not been explored in depth in previous studies on organizational learning. However, work on different *sources of information* has underscored that in some settings different sources of information may work together to enhance each other's impact on behavior (Taylor and Greve 2006). Haleblian et al. (2006) reported that the interaction of the *number of prior acquisitions* and the *performance feedback from prior acquisitions* affects the likelihood of making subsequent acquisitions. This finding provided evidence that two information sources—i.e., prior experience of making acquisitions and how well firms performed in the prior acquisitions—jointly shape future acquisition behavior. Haunschild and Beckman (1998) found that the properties of several information sources jointly determined firm behavior, with some serving as complements and others as substitutes. We advance this line of research by theorizing and testing how the presence of both success and recovery experience will affect the value of each type of experience. Specifically, we theorize that in this context the two types of experience should enhance rather than substitute for each other's impact, helping overcome limitations of each source of learning.

In the previous sections, we predicted challenges and harmful learning outcomes when firms have some success and recovery experience but lack sufficient prior experience of the same type to overcome the dangers of limited experience. Emerging organizational learning research increasingly argues that firms can learn more effectively and overcome learning dangers when they learn from diverse experiences (March et al. 1991, Zollo and Winter 2002). For example, Haunschild and Sullivan (2002) found that airlines that experienced more heterogeneous causes of prior errors suffered a lower subsequent number of errors and attributed this finding to the benefits of diverse experience. Schilling et al. (2003) found that variation in experience improved learning rates in a problem-solving experimental setting. These studies build on classic theories of statistical inference that suggest that high variability in a firm's experience helps it to make more accurate inferences about actions and outcomes. Similarly, we propose that success and recovery experience will enhance each others' value.

From the learning perspective, recovery and success experience represent a particularly promising combination of diverse experiences. We have noted that success and recovery experience are both likely to draw a great deal of organizational attention. In particular, the presence of little prior experience of a given type will tend to pull decision-makers' attention in one extreme direction, creating biases in interpretation and generating potentially harmful actions as outlined above. However, this problem can be mitigated by combining opposite types of experience that can help balance decision-makers' cognitive maps. Theories of associative learning suggest that events or ideas can be better understood when contrasting information is present (Sternberg 2003). The availability of contrasting information enhances the effectiveness of experiential learning by reducing causal ambiguities and uncertainties surrounding the experienced outcomes (Morris and Moore 2000). When learning occurs from both recovery and success experiences, a firm gains an opportunity to compare information about both patterns. It can cross-check for consistency in activities related to avoiding failure and achieving success with a richer palate of events and actions to draw on for causal models of its own history. These ongoing comparisons permit the firm to gain a larger library of possibly valuable activities available to deploy if surprising external events should occur (Feldman 1989, Walsh and Ungson 1991). This will also help the firm to identify successful and unsuccessful routines more accurately and to improve its theories about actions leading to success or failure.

We have argued that it is difficult to learn effectively from success or recovery experience alone because the small sample size for such rare experience limits its ability to draw valid inferences. The paucity of contextual information for interpretation induces more error in interpreting the events (March et al. 1991). We have previously contended that these potential challenges can be overcome by accumulating more of the same type of experience. Valid inferential learning from experience requires estimating the underlying distribution from which the experience is drawn (March et al. 1991). As the sample size increases, expected errors decrease, and firms can derive more reliable and valid lessons. However, it is not always possible to increase the sample size when firms learn from rare forms of experience such as recovery and unusual success. It is unlikely that firms actively seek to accumulate failure-related experience such as recovery experiences. The presence of both types of experience offers an alternative source of relevant information and allows firms to triangulate their findings and complement the deficiencies of each type of experience.

Learning exclusively from either success or distress also can lead a firm to a myopic learning process, in which organizations focus on knowledge with short-term or local value but limit their search for knowledge that could have greater value (Levinthal and March 1993). Firms learning from success and recovery experience alone may focus on apparently successful prior actions, in each case failing to search more broadly for possible better solutions. Such unbalanced and limited search behavior may result in the adoption of suboptimal routines or even hurt long-term performance or survival (Gupta et al. 2006, March 1991). Consistent with these arguments, prior models have suggested that a more precise cognitive map arising from contrasting experiences will also lead to more intelligent search behavior (Gavetti and Levinthal 2000). Comments by a senior bank manager whom we interviewed illustrate this possibility:[4]

> We did very well during the past few years, mainly thanks to the hot real estate market here on the West Coast. We are likely to continue to focus on that market next year. It is hard to turn your back on profit opportunities. But there are some concerns about the increasing risk profile of this market segment, and some believe we could repeat the same crisis we experienced when the real estate market collapsed fifteen years ago [the early '90s]. But I don't think there will be a serious crisis this time even if the market crashes because we are not simply banking on the real estate boom. We are much better equipped to deal with a similar crisis. After all, many of us paid our dues.

This remark underscores the potential for enhanced value of learning from both success and recovery experience over either alone. The manager perceived prior crises as helping the firm avoid pitfalls of the current success and be better prepared for potential future crises.

The arguments above imply that success experience and recovery experience will each enhance the learning value of the other. Thus, we propose that the joint presence of success and recovery experience should produce more positive survival-enhancing learning than the presence of either experience alone.

HYPOTHESIS 3. *Success and recovery experience interact with each other such that the* greater *one type of experience of a focal bank, the* more negative *the relationship between the other type of experience and the failure rate of the bank.*

Methods

Study Setting and Sample

We explored our research questions using a sample consisting of all of the Federal Deposit Insurance Corporation (FDIC)-insured U.S. commercial banks founded during the 15-year period between January 1, 1984, and December 31, 1998. We identified 2,724 banks chartered during the study period; of those, 28 banks were dropped from the sample due to incomplete data. During the study period, 259 of the remaining 2,696 banks failed, and 905 banks were right-censored from the sample because of mergers and acquisitions; the remaining 1,532 banks remained active as of December 31, 1998.

We obtained the bank financial and demographic data from IDC Financial Publishing (IDC), a commercial banking industry analysis firm. We collected additional demographic and regulatory data from sources including the SNL Financial's Bank Regulatory Database, the Federal Reserve Board, the Office of Comptroller of the Currency, and the FDIC.

To test theories about how firms have learned from recovery and success experience since their founding, we needed a complete history of banks' financial data to account for all of the experience each bank had accumulated since its founding. The complete financial data were not available before 1984, so we could not measure the complete history of recovery and success experience of banks chartered before 1984. Thus, we used a cohort sample of banks chartered since 1984 to accurately capture the complete history of experiences of the banks in the sample. Because these cohort banks were new firms when they entered the sample, they started with no prior organization-level success or recovery experience. Thus, they offer a chance to explore the impact of these experience types in the presence of little or no prior experience and to test theory about the impact of additional experience of the same type.

This setting also provides several other valuable features for this study. The banking industry offers standardized performance ratings that have direct bearing on firm survival. The historic regulation of the industry provides rich data on performance hierarchy (i.e., strong performance, normal performance, or distress). The system is objectively set by industry norms using the CAMEL rating, a composite index that measures the financial soundness and performance of banking institutions that is widely accepted in the banking industry. This industry feature makes it possible to objectively define success and distress of banks.

Although the failure rates of new firms in the banking industry (approximately 10% for our entire sample period) are not extremely high, failure is a very important issue for this industry. Bank failure is costly not only for the failed banks and their direct stakeholders but also for society as a whole because federal and state governments must assume much of the loss by paying out deposit insurance claims with taxpayers' money. Furthermore, banks pay a great deal of attention to issues that could increase their risk of failure because banks that are perceived to be at high risk of failure are subject to many competitive disadvantages, including higher borrowing rates, funding problems, frequent regulatory sanctions, and difficulties in attracting deposits due to low customer confidence (Hanc 1997). Our field data and industry histories provide ample anecdotal evidence that bankers pay close attention to learning and to developing strategies that will minimize the chance of failure, and the relatively low failure rates of banks are often attributed to these learning efforts (FDIC 1997).

The possibility of failure is especially salient for new banks because new banks pass through a period of financial fragility during which they are more vulnerable to failure than established institutions (DeYoung and Hasan 1998, Hunter and Srinivasan 1990). Thus, the operational focus of new banks often involves improving their chances of survival rather than high profitability by raising their capital level, building up financial reserves, educating employees for risk management, and building a safety network (DeYoung 2003). Because survival is such a pressing issue for new banks, this industry offers an appropriate context for studying survival-enhancing learning.

Finally, the study setting enhances the broader value of this research. Because the banking industry is a critical part of the national economic system, its performance has a broad impact as evidenced by the massive impacts of the recent subprime mortgage crisis on the banking system and the world economy; this makes the banking industry an important setting for studying survival-enhancing learning. Furthermore, although this is a very mature, well-established industry, entrepreneurial activity continuously occurs through many newly chartered banks, as evidenced by the more than 2,700 new banks founded during our study period alone. Industry observers consider these new entrants to be important for maintaining the viability of the entire industry because they help restore competition in local markets that have experienced consolidation and serve as credit replacements for small businesses whose banks were closed or acquired (DeYoung 1999).

Analysis of Bank Failure

The dependent variable is the *unobserved hazard rate of failure* of banks in the sample. Banks were considered to have failed if they were (1) liquidated or (2) merged with another bank with FDIC financial assistance. Failure was recorded quarterly at the end of each quarter. Liquidating or closing a bank is very costly, not only for the banks that failed but also for the general public because the FDIC must pay the deposit insurance claims with federal funds. Thus, when a bank is on the verge of failing due to serious financial or managerial problems, the FDIC typically searches for a potential acquirer to avoid liquidation, and they provide financial assistance to the acquiring bank to incentivize the transaction. Banks acquired with financial assistance are virtually dissolved in most cases, and only their assets and/or branches are absorbed by the acquiring banks. Thus, the FDIC formerly classifies such transactions as bank failure (FDIC 1997). Voluntary, non-FDIC-assisted mergers and acquisitions that were not associated with failure were not treated as failures but as being right-censored.

In our sample, 57% of the banks were right-censored without experiencing any event by the end of the study period (1,532/2,696 total banks in the sample), and 34% of the banks (905/2,696) were censored from the sample due to an event other than failure (i.e., acquisition). This makes it important to use a statistical technique that provides unbiased failure rate estimates by taking into account right-censored cases. Survival analysis uses all of the information provided by right-censored cases and avoids parameter estimation bias caused by right-censored observations.

We used a piecewise exponential model, which provides a flexible functional form of age dependence (Baum and Ingram 1998, Yamaguchi 1991). The piecewise exponential model splits the age of the firms in the sample into predefined age segments and assumes that the hazard rates are constant within each time segment, but it allows the hazard function to vary between the time segments (Blossfeld and Rohwer 2002). We created three age segments (i.e., zero to four years, five to eight years, and nine years or older) because our preliminary data analysis, including Kaplan-Meyer estimation, detected two discontinuities in hazard rates corresponding approximately to the fourth and ninth years after founding. These age periods are consistent with prior banking research (DeYoung 2003). We also estimated our models using different cutoff points and obtained consistent results.

To examine whether our findings are sensitive to model specification, we estimated models using

Gompertz, Weibull, and simple exponential (without time pieces) models, which use different parametric assumptions of age dependence on failure rates. We also estimated models using the semiparametric Cox proportional hazards model. Although our data do not satisfy the proportional hazard assumption of the Cox model, these estimations can shed light on the results obtained from the parametric models (Cleves et al. 2002). Results for these models with alternative specifications were consistent with the results obtained from the piecewise exponential model, indicating the fact that our findings are not an artifact of a specific parametric assumption.

Independent Variables

Success Experience. We define a success experience as occurring when a bank in the sample experienced unusually strong performance. A bank's performance level was measured by its CAMEL rating, a composite index that assesses the five most important areas of financial and management performance of a bank: capital risk, asset quality, margins, earnings, and leverage. We use CAMEL ratings that were computed by IDC.[5]

The IDC CAMEL rating is highly consistent with the official CAMEL rating maintained by the FDIC, which is not available to the public, because they are computed based on the same principles, and it has been shown to have high predictive validity for assessing the likelihood of bank failure (IDC Financial Publishing 2002). We also compared the IDC CAMEL ratings with the VERIBANC rating, another widely used bank rating system, and we found that they are highly consistent. The IDC CAMEL rating ranges from 1 (the lowest) to 300 (the highest). The IDC CAMEL rating of 200 or higher corresponds to the highest FDIC CAMEL rating category,[6] which the banking industry considers to be very high (Curry et al. 2001). Thus, a bank was defined as being successful when it obtained a CAMEL rating of 200 or higher in a given quarter. Although this threshold is widely accepted for defining success and/or strong performance in the banking industry, we performed a sensitivity analysis to examine whether our results are robust across different cutoff points for defining success. Specifically, we estimated models with success variables defined by two different cutoff values around 200 (e.g., 190 and 210), and we obtained consistent results.

Experience accumulates over time, but organizational learning research indicates that lessons learned from past experience may not increase monotonically because the value of such lessons may depreciate over time (Argote 1999). Prior studies usually discounted past experience, using a prespecified functional form such as the age of the experience. Similarly, we discounted success experience, using the age of each experience (Ingram and Baum 1997). We also estimated models using experience variables that were discounted by alternative discount factors—i.e., no discount, age-squared (age^2), and age-square root ($\sqrt{age}$)—to examine the robustness of our findings. We found consistent results from these alternative specifications. Because success experience was constructed based on quarterly data, the age of experience was measured quarterly. Thus, *success experience* of a bank i at time t was operationalized as the discounted sum of the total number of quarters in which the bank i recorded a CAMEL rating of 200 or higher since its charter (t_c):

$$\textit{success experience} = \sum_{j=t_c}^{t-1} (\textit{success experiences}_{ij} / \textit{discount factor}),$$

where t_c is the quarter that bank i was chartered, *success experience*$_{ij}$ is an indicator of whether bank i experienced success in quarter j, and *discount factor* is the age of the experience.

Recovery Experience. We define a recovery experience as occurring when a bank that experiences a critical financial distress that puts it at high risk of failure overcomes the crisis and returns a normal level of performance. The CAMEL rating is more appropriate than other performance indicators for measuring recovery experience because it is directly associated with the risk of a bank's failure (Meyer and Vaughan 2000). A bank with a CAMEL rating below 125 is considered to be under severe financial strain and at high risk of failure. The IDC CAMEL ratings below 125 correspond to 4 or 5 on FDIC's official CAMEL rating scale, and FDIC classifies banks with an FDIC CAMEL rating of 4 or 5 as being severely distressed (Curry et al. 2001). This level is a well-accepted indicator of bank distress in the industry (Office of Inspector General 2006).

Building on the banking literature and prior studies on organizational learning (Gunther and Moore 2000, Kim and Miner 2007), we operationalized each recovery experience as occurring when a bank's CAMEL rating drops below 125 for at least two consecutive quarters, then moves up to a rating higher than 125. It is very undesirable for a bank to receive a low rating for an extended period of time because a persistently low rating will eventually trigger regulatory intervention that may result in a closure or a forced merger. Thus, receiving a low rating for more than two quarters usually indicates that the bank has serious managerial issues.

Recovery experience for bank i at time t was operationalized as the discounted sum of the total number of individual recovery experiences that a bank has accumulated since its charter (t_c):

$$\textit{recovery experience} = \sum_{j=t_c}^{t-1} (\textit{recovery experience}_{ij} / \textit{discount factor}).$$

Control Variables

We included an extensive set of control variables to systematically account for potential alternative factors that could affect the failure of banks in the sample other than organizational learning.

Organizational Characteristics. This set of variables helps control for potential heterogeneity among banks. We included *bank size*, measured by the logarithm of the total assets of a bank because firm size can affect the survival chances of a firm (Baum 1996). The charter type of a bank determines the type of regulations and statutory constraints that the bank is subject to, which in turn influences the various aspects of the bank's operation and characteristics. Thus, we included *charter type*, an indicator of whether a bank was federally chartered (coded 1) or state chartered (coded 0). Capital level can also significantly influence the probability of bank failure (Dietrich and James 1983). Undercapitalized banks are more likely to fail when a serious management and/or financial problem (e.g., a large sum of default loans) arises. Thus, we added *capital asset ratio*, measured by the ratio of equity capital to total assets, to control for capital risk. Because the financial performance of a bank has a direct impact on the survival of the bank, we included the logarithm of *CAMEL rating* to capture a bank's financial performance and conditions. CAMEL rating was log-transformed because we assumed a decreasing marginal effect of the CAMEL rating on failure rates.[7] Using the CAMEL rating without log-transformation did not change the results. A high CAMEL rating generally produces positive effects on bank survival, and the vast majority of failed banks (>90%) in our sample had a very low rating (0–125) at the time of failure. However, a very small number of banks with a very high rating also failed. Thus, we included *high CAMEL failure*, a firm-level dummy variable that indicates banks that failed with a CAMEL rating of 200 or higher, to control for the possibility that these banks are systematically different from other banks in the sample. A sharp drop in the CAMEL rating may indicate serious management or financial problems and may increase the risk of bank failure. Thus, we included *CAMEL change*, which was measured by the change in CAMEL rating from the previous quarter, to control for this potential effect. All organizational-level variables were measured quarterly.

Industry and Environmental Conditions. The number of firms in an industry often determines the level of competition, which influences the survival chance of the firms in that industry. Thus, we included *bank density* and *bank density*^{2}. Because the majority of banks in our sample operated in a single state during the study period, we used the states to define the boundary of competition. *Bank density* was operationalized as the total number of banks that operated in the state in which the focal bank was located in a given quarter.[8]

Macroeconomic conditions and social environments can also have a substantial impact on a firm's survival. We included *unemployment rate* and *personal income*, which were measured respectively by the unemployment rate and the per capita average personal income of the state in which the focal bank is located, to control for the general economic conditions of a focal bank's geographic market. During the study period, many bank failures were attributed to unfavorable shifts in the real estate market (Freund et al. 1997), so we controlled for potential effects of the real estate market by including the *National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index*, which represents a measure of real estate performance calculated quarterly, based on the total rate of return of investment in commercial real estate properties acquired in the private market for investment purposes. These three variables were all measured at the state level because most banks in the sample operated in a single state. *Bank prime loan rate*, the base rate on corporate loans posted by at least 75% of the nation's 30 largest banks, was also included to control for the effects of overall financial market conditions.

Finally, we included *calendar time* to rule out any potential effect of time trends. *Calendar time* was measured by the number of months that have passed since January 1, 1984, the starting time of this study, until the time of the focal observation.

Operating Experience. Operating experience has been recognized as an important source of learning, and ample empirical evidence exists to show that it can influence firm performance (Argote and Epple 1990). A firm's operating experience can be measured by its cumulative experience associated with its core activities. In the commercial banking context, loans are the most important portion of business for most banks, and the bulk of operation activities are either directly or indirectly related to loans, including securing funds for loans, and selling and managing loans (Hebeka 2005). Hence, the amount of loans a bank has made since its charter is a good proxy of the bank's total operating experience. *Operating experience* was operationalized as the discounted (by age) sum of the total dollar value of loans that a bank made since its charter. Prior studies argue that a very high level of operating experience may actually harm firms' performance by leading them into a competency trap (Baum and Ingram 1998). Thus, we included operating experience and its squared term in our models.

Congenital Industry-Level Experience. Firms can learn not only from the contemporary experience they have acquired since their founding but also from the stock of experience that has accrued within an industry before their birth, often referred to as congenital experience (Argote 1999, Huber 1991). We included *congenital failure experience*, which was measured by the discounted (by age) sum of the total number of bank failures in the same state in which the focal bank operated since 1934 (the year in which FDIC was established) to the year before the focal bank was founded. We also included *congenital operating experience*, which proxies the amount of knowledge that the banking industry has accumulated through normal operations. This was measured by the discounted (by age) sum of the total amount of loans made by all the banks in the same state in which the focal bank operated since 1966, the year state level loan data became available, to the year before the focal bank was founded.

Industry-Level Failure and Recovery Experience. Banks can learn from observing the experience of other banks. *Industry failure experience* was operationalized as the discounted (by age) sum of the total number of bank failures in the same state in which the focal bank operated since a focal bank's founding. We also included *industry recovery experience*, which was measured by the discounted (by age) sum of the total number of recovery events that all of the banks in the same state in which the focal bank operated since a focal bank's founding. These industry-level variables have been shown previously to influence survival-enhancing learning (Kim and Miner 2007), making them important to control for in this study of a firm's own experience.

To check if our findings are sensitive to the choice of control variables, we performed extensive sensitivity analysis by including different combinations of both the current control variables and alternative control variables. Our core findings were insensitive to the choice of control variables.

Results

Table 1 shows descriptive statistics and a bivariate correlation matrix for all study variables. The bivariate correlation coefficients among the variables are generally in the low to moderate range. A low to moderate level of multicollinearity does not cause a bias in parameter estimation, although it may cause less-efficient parameter estimates by inflating standard errors, making it less likely that statistically significant results will appear in some cases, and possibly causing instability in coefficients (Cohen and Cohen 1983, Greene 2003). To address any potential multicollinearity concern, we calculated variance inflation factors (VIFs) for all variables; the average VIF was 5.53 for the model without interaction variables (Model 3, Table 2), and the individual VIFs ranged between 1.01 and 16.11. The higher VIFs that exceed 10—one general rule of thumb for assessing multicollinearity—were observed for the linear and squared terms for our success and recovery variable. The linear term and the squared term of a variable are typically highly correlated. Because curvilinear success and recovery experience effects represent key theoretical predictions, we used both the linear and the squared terms in the models. Finally, models including multiplicative interaction terms typically show high levels of collinearity. When the VIFs were calculated with all of the interaction variables (Model 5), the average VIF increased to 8.37, a value that does not raise serious concerns for multicollinearity. We estimated models using interactions of mean-centered variables as suggested by Aiken and West (1991), and we obtained consistent results. Furthermore, we did not detect instability in regression coefficients for the baseline and study variable models when interaction variables were individually added (Models 4 and 5).

Table 2 reports maximum-likelihood estimates of the bank failure rate using the piecewise exponential model. Significance tests shown in the table are two-tailed for all variables. The baseline model contains all of the control variables. Research variables (i.e., *success experience, recovery experience*, and their squared terms) were hierarchically added to Models 1–3. Model 4 adds the linear interaction between *success experience* and *recovery experience* hierarchically to Model 3. Model 5 presents the fully saturated model with all four possible combinations of interactions between *success experience* and *recovery experience*. It is useful to keep in mind that because the baseline model controls for the time since an organization was born, the experience variables capture experience itself and are not a proxy for age. Because the effects of time since founding, then, are already factored into the models, the results for experience do not simply represent the impact of the new firms getting older.

Success Experience. Hypothesis 1 predicted that success experience will first increase failure but that above a certain level it will decrease it, creating an inverted U-shaped relationship between *success experience* and the failure rates. This prediction was supported. The coefficient for *success experience* is positive and statistically significant in all of the models, and its squared term is negative and statistically significant in all of the models except Model 3. That is, success at first increases the likelihood of mortality and then decreases it. Because the hierarchical models with interaction terms led to better model fit, Model 3, without the interaction terms, is underspecified. Thus, we used the saturated model for assessment of its total effect. The data range of *success experience* was between 0 and 4.61, and the inflection point lies at 2.79. To determine whether the quadratic effects we observed occurred at a meaningful value, we calculated the inflection point and estimated its 95% confidence interval. The symmetric 95% confidence interval for the inflection point for *success experience* is between 2.20 and 3.39, which is well within the

Table 1 Descriptive Statistics and Bivariate Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8
1 *Age* 0–4 years	0.43	0.49								
2 *Age* 4–9 years	0.40	0.49	−0.71							
3 *Age* >9 years	0.17	0.37	−0.39	−0.37						
4 *Calendar time* (Months)	108.76	44.94	−0.47	0.13	0.45					
5 *Bank size* (log[$000])	10.73	1.16	−0.30	0.14	0.21	0.40				
6 *Charter type*	0.38	0.48	0.01	−0.02	0.02	−0.15	−0.04			
7 *Capital asset ratio*	0.15	1.17	0.04	−0.03	−0.02	−0.01	−0.05	0.01		
8 *CAMEL rating*	4.70	1.25	−0.08	−0.03	0.14	0.32	0.22	−0.14	−0.03	
9 *CAMEL change*	−0.19	28.11	−0.07	0.05	0.02	0.03	0.03	0.00	0.00	0.11
10 *High CAMEL failure*	0.01	0.08	0.03	−0.01	−0.03	−0.08	0.00	0.04	0.02	−0.01
11 *Bank density*	470.40	448.57	0.15	−0.08	−0.09	−0.40	−0.26	0.28	−0.01	−0.27
12 *Bank density*^{2} (/1,000)	422.48	815.04	0.20	−0.12	−0.11	−0.42	−0.23	0.27	0.00	−0.27
13 *Unemployment rate* (%)	5.93	1.58	0.10	0.05	−0.19	−0.42	−0.16	0.14	−0.01	−0.01
14 *Personal income* ($000)	20.43	4.30	−0.36	0.10	0.34	0.78	0.40	−0.17	−0.01	−0.01
15 *Bank prime loan rate* (%)	8.33	1.40	0.20	−0.17	−0.04	−0.30	−0.13	0.06	0.01	−0.14
16 *NCREIF index*	1.45	1.81	−0.06	−0.17	0.29	0.36	0.12	−0.02	0.01	0.14
17 *Congenital failure exp*	8.44	21.24	0.03	0.00	−0.04	0.03	0.08	0.06	−0.01	−0.01
18 *Congenital operating exp* ($B)	180.00	205.00	−0.01	0.01	0.01	0.05	0.08	0.05	−0.00	0.00
19 *Industry failure exp*	21.47	45.74	−0.20	0.17	0.03	−0.09	−0.07	0.22	−0.02	−0.18
20 *Industry recovery exp*	87.98	92.15	−0.32	0.16	0.21	0.03	−0.04	0.23	−0.04	−0.08
21 *Operating experience*	0.37	3.63	−0.04	0.02	0.02	0.07	0.36	0.05	0.00	0.04
22 *Operating experience*^{2}	13.29	702.70	−0.01	0.01	−0.00	0.02	0.12	0.02	0.00	0.01
23 *Success experience*	0.82	1.08	−0.16	−0.01	0.22	0.33	0.19	−0.12	0.01	0.39
24 *Success experience*^{2}	1.84	3.48	−0.20	0.03	0.24	0.32	0.21	−0.10	0.01	0.32
25 *Recovery experience*	0.10	0.22	−0.14	0.09	0.07	0.05	0.01	0.04	−0.02	0.01
26 *Recovery experience*^{2}	0.06	0.21	−0.06	0.05	0.01	0.01	−0.01	0.03	−0.01	−0.03
27 *Success exp ∗ recovery exp*	0.04	0.11	−0.16	0.02	0.19	0.14	0.06	0.00	−0.01	0.15
28 *Success exp*^{2} ∗ *recovery exp*	0.06	0.21	−0.17	0.00	0.23	0.17	0.09	−0.01	−0.01	0.17
29 *Success exp ∗ recovery exp*^{2}	0.01	0.07	−0.04	0.01	0.05	0.03	−0.01	0.00	0.00	0.05
30 *Success exp*^{2} ∗ *recovery exp*^{2}	0.01	0.09	−0.05	0.00	0.07	0.04	0.01	0.00	0.00	0.08

Table 1 (cont'd.)

	9	10	11	12	13	14	15	16	17	18	19
10 *High CAMEL failure*	0.00										
11 *Bank density (11,000)*	0.00	−0.01									
12 *Bank density*^{2} (/1,000)	0.00	0.00	0.95								
13 *Unemployment rate* (by state)	−0.01	−0.01	0.36	0.37							
14 *Personal income* (by state)	0.01	−0.05	−0.40	−0.40	−0.36						
15 *Bank prime loan rate*	−0.02	0.04	0.13	0.13	−0.23	−0.20					
16 *NCREIF index* (by state)	0.02	−0.01	−0.12	−0.10	−0.40	0.30	0.29				
17 *Congenital failure exp*	0.02	−0.02	0.28	0.20	0.08	−0.03	−0.02	−0.01			
18 *Congenital operating exp*	−0.01	−0.03	0.22	0.17	0.28	0.27	−0.03	0.00	0.15		
19 *Industry failure exp*	0.03	−0.02	0.12	0.38	0.21	−0.16	0.04	−0.12	0.25	0.19	
20 *Industry recovery exp*	0.03	−0.03	0.61	0.43	0.18	−0.07	−0.10	−0.05	0.30	0.20	0.77
21 *Operating experience*	0.01	0.00	−0.03	−0.02	−0.04	0.06	−0.01	0.04	0.10	0.00	0.01
22 *Operating experience*^{2}	0.00	0.00	−0.01	0.00	−0.02	0.01	0.00	0.02	0.03	0.00	0.00
23 *Success experience*	0.00	0.03	−0.18	−0.17	−0.22	0.23	−0.06	0.21	0.05	−0.02	−0.10
24 *Success experience*^{2}	0.00	0.02	−0.15	−0.14	−0.19	0.21	−0.05	0.20	0.05	−0.03	−0.07
25 *Recovery experience*	0.23	−0.02	0.03	0.01	0.02	0.03	−0.06	−0.01	0.00	0.00	0.08
26 *Recovery experience*^{2}	0.25	−0.01	0.03	0.02	0.02	0.00	−0.04	−0.02	0.00	0.00	0.05
27 *Success exp ∗ recovery exp*	0.19	0.00	−0.01	−0.02	−0.07	0.09	−0.05	0.08	0.05	−0.01	0.04
28 *Success exp*^{2} ∗ *recovery exp*	0.11	0.00	−0.02	−0.03	−0.10	0.11	−0.04	0.11	0.06	−0.03	0.03
29 *Success exp ∗ recovery exp*^{2}	0.27	0.00	0.01	0.01	−0.01	0.02	−0.02	0.02	0.19	0.01	0.02
30 *Success exp*^{2} ∗ *recovery exp*^{2}	0.22	0.01	0.01	0.01	−0.02	0.03	−0.01	0.04	0.03	−0.00	0.02

Table 1 (cont'd.)

	20	21	22	23	24	25	26	27	28	29
21 *Operating experience*	0.00									
22 *Operating experience²*	0.00	0.82								
23 *Success experience*	−0.04	0.06	0.02							
24 *Success experience²*	−0.01	0.06	0.01	0.95						
25 *Recovery experience*	0.12	−0.01	−0.01	−0.19	−0.16					
26 *Recovery experience²*	0.06	−0.01	0.00	−0.16	−0.13	0.94				
27 *Success exp ∗ recovery exp*	0.10	0.01	0.00	0.26	0.18	0.36	0.26			
28 *Success exp² ∗ recovery exp*	0.10	0.02	0.00	0.39	0.34	0.16	0.07	0.89		
29 *Success exp ∗ recovery exp²*	0.03	0.00	0.00	0.04	0.00	0.45	0.44	0.79	0.52	
30 *Success exp² ∗ recovery exp²*	0.04	0.00	0.00	0.12	0.07	0.27	0.24	0.82	0.70	0.89

Table 2 Piecewise Exponential Estimation of Bank Failure ($N = 63{,}036$)

Variable	Baseline	Model 1	Model 2
Period & calendar time			
Age 0–4 year	0.3562 (0.541)	0.3813 (0.542)	0.3883 (0.556)
Age 4–9 year	0.9231* (0.492)	0.9082* (0.493)	0.8600* (0.513)
Age >9 year	−3.4113** (1.538)	−3.4472** (1.553)	−4.9915*** (1.586)
Calendar time	0.0040 (0.005)	0.0015 (0.005)	−0.0034 (0.005)
Organizational-level control variables			
Bank size	−0.3558*** (0.100)	−0.3250*** (0.098)	−0.2130* (0.112)
Charter type	0.2585* (0.146)	0.3357** (0.149)	0.2510* (0.144)
Capital asset ratio	−0.0071 (0.030)	−0.0078 (0.031)	0.0245* (0.015)
CAMEL rating	−0.9616*** (0.047)	−1.1927*** (0.071)	−0.8963*** (0.051)
CAMEL change	−0.0003 (0.004)	0.0020 (0.003)	−0.0097*** (0.003)
High CAMEL failure	1.9999*** (0.270)	1.9053*** (0.269)	4.4484*** (0.335)
Industry & environment control variables (all measured by state except for *bank prime loan rate*)			
Bank density	−0.0004 (0.001)	−0.0001 (0.001)	0.0020** (0.001)
Bank density²	0.0001 (0.000)	0.0000 (0.000)	−0.0007* (0.000)
Unemployment rate	0.1218** (0.053)	0.1144** (0.055)	0.0114 (0.054)
Personal income	0.0453 (0.031)	0.0458 (0.031)	0.0231 (0.028)
Bank prime loan rate	0.0329 (0.058)	0.0065 (0.058)	−0.1361** (0.061)
NCREIF index	−0.1370*** (0.037)	−0.1343*** (0.037)	−0.0271 (0.038)
Congenital experience			
Congenital failure experience	0.0106*** (0.002)	0.0105*** (0.002)	0.0187*** (0.002)
Congenital operating experience	−0.0001 (0.001)	−0.0001 (0.001)	0.0004 (0.001)
Industry-level experience			
Industry failure experience	0.0010 (0.002)	0.0013 (0.002)	0.0039** (0.002)
Industry recovery experience	−0.0004 (0.002)	−0.0008 (0.002)	−0.0089*** (0.002)
Own operating experience			
Operating experience	1.9510*** (0.744)	1.5610** (0.662)	1.3752* (0.741)
Operating experience²	−0.4726 (0.291)	−0.3519 (0.222)	−0.3437 (0.240)
Own success and recovery experience			
Success experience		2.0551*** (0.410)	
Success experience²		−0.3641*** (0.122)	
Recovery experience			9.7304*** (1.272)
Recovery experience²			−4.1957*** (1.142)
Interaction terms			
Success exp ∗ recovery exp			
Success exp² ∗ recovery exp			
Success exp ∗ recovery exp²			
Success exp² ∗ recovery exp²			
Log Likelihood	−1,312.679	−1,292.662	−836.482
Likelihood ratio test (χ^2)[a]		40.034***	912.36***
Akaike information criteria	695.823	659.788	−252.573
Bayesian information criteria	885.903	867.972	−44.389

Table 2 (cont'd.)

Variable	Model 3	Model 4	Model 5
Period & Calendar time			
Age 0–4 year	0.5365 (0.564)	0.2442 (0.560)	0.2428 (0.559)
Age 4–9 year	0.8967* (0.518)	0.6954 (0.516)	0.6969 (0.515)
Age >9 year	−6.6290***(1.650)	−6.9080***(1.664)	−6.8111***(1.672)
Calendar time	−0.0021 (0.005)	−0.0010 (0.005)	−0.0010 (0.005)
Organizational-level control variables			
Bank size	−0.1002 (0.115)	−0.1172 (0.116)	−0.1330 (0.118)
Charter type	0.3159** (0.146)	0.2797* (0.145)	0.2771* (0.145)
Capital asset ratio	0.0254* (0.015)	0.0298** (0.015)	0.0301** (0.015)
CAMEL rating	−1.0848***(0.067)	−1.2298***(0.084)	−1.2156***(0.084)
CAMEL change	−0.0078***(0.003)	−0.0032 (0.003)	−0.0031 (0.003)
High CAMEL failure	4.4209***(0.352)	4.6571***(0.369)	4.7075***(0.374)
Industry & environment control variables (all measured by state except for *bank prime loan rate*)			
Bank density	0.0029***(0.001)	0.0035***(0.001)	0.0036***(0.001)
Bank density^2	−0.0010***(0.000)	−0.0013***(0.000)	−0.0013***(0.000)
Unemployment rate	0.0056 (0.056)	0.0150 (0.053)	0.0179 (0.053)
Personal income	0.0121 (0.028)	0.0122 (0.028)	0.0135 (0.028)
Bank prime loan rate	−0.1281** (0.061)	−0.1418** (0.060)	−0.1466** (0.060)
NCREIF index	−0.0258 (0.038)	−0.0306 (0.038)	−0.0292 (0.038)
Congenital experience			
Congenital failure experience	0.0171***(0.002)	0.0187***(0.002)	0.0189***(0.002)
Congenital operating experience	0.0003 (0.001)	0.0002 (0.001)	0.0002 (0.001)
Industry-level experience			
Industry failure experience	0.0045***(0.002)	0.0043** (0.002)	0.0044** (0.002)
Industry recovery experience	−0.0111***(0.002)	−0.0124***(0.002)	−0.0127***(0.002)
Own operating experience			
Operating experience	1.0271 (0.743)	1.2890* (0.736)	1.3418* (0.741)
Operating experience^2	−0.2802 (0.207)	−0.3506* (0.209)	−0.3628* (0.213)
Own success and recovery experience			
Success experience	1.5295***(0.402)	4.4082***(0.645)	4.4179***(0.654)
Success experience^2	−0.0279 (0.116)	−0.7789***(0.180)	−0.7910***(0.188)
Recovery experience	10.0546***(1.328)	12.4729***(1.522)	13.2515***(1.864)
Recovery experience^2	−4.1946***(1.200)	−5.8422***(1.354)	−6.5993***(1.699)
Interaction terms			
Success exp ∗ *recovery exp*		−4.0990***(0.749)	−7.0876 (6.916)
Success exp^2 ∗ *recovery exp*			1.4832 (2.740)
Success exp ∗ *recovery exp*^{2}			3.9142 (6.464)
Success exp^2 ∗ *recovery exp*^{2}			−3.2963 (3.149)
Log Likelihood	−804.922	−788.891	−788.153
Likelihood ratio test (χ^2)[a]	63.12***	32.062***	1.476
Likelihood ratio test (χ^2)[b]		32.062***	33.538***
Akaike information criteria	−311.692	−341.753	−337.229
Bayesian information criteria	−85.405	−106.415	−74.737

Notes. Standard errors are shown in parenthesis.
[a]The likelihood ratio tests were performed based on the comparisons with the immediate preceding models.
[b]The likelihood ratio tests for Models 4 and 5 contrast these models with Model 3, which contains no interaction term.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. All significant tests are two-tailed.

sample data range (0–4.61). Thus, the curvilinear effects we observed were not an artifact of extrapolating the model (Weesie 2001).

Recovery Experience. Hypothesis 2 predicted that *recovery experience* will also initially increase failure but then reduce it, generating an inverted U-shaped effect on the failure rates of the sample banks. The coefficient for *recovery experience* is positive and statistically significant, and its squared term is negative and statistically significant in all models, including the fully saturated model and all other models examining interaction effects. The inflection point for *recovery experience* was 1.00, which is within the sample data range (0–1.41), with the 95% confidence interval covering the range from 0.77 to 1.24. This indicates that the curvilinear effects occurred at a meaningful value that falls within the range of our sample values (Weesie 2001).

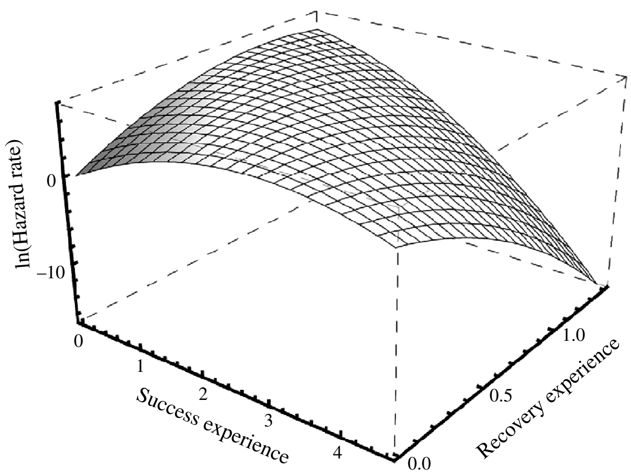
Interaction Between Success and Recovery Experience. Testing an interaction between variables with higher-order effects is complex, and there is a debate about the appropriate methods of modeling higher-order interaction effects (Aiken and West 1991). The interaction effect between *success experience* and *recovery experience* can be tested in two ways: (1) capturing the total effect of the interaction by including all possible combinations of the two variables, and (2) interpreting the interaction based only on the interaction terms that significantly contribute to model improvement.

The first method involves including all four possible combinations of the variables (*success experience* $*$ *recovery experience* [SR], *success experience*^{2} $*$ *recovery experience* [S^2R], *success experience* $*$ *recovery experience*^{2} [SR^2], and *success experience*^{2} $*$ *recovery experience*^{2} [S^2R^2]) to capture the total effect of the interaction. The significance of the overall interaction effect can be determined by performing the likelihood ratio test for all four terms together. The likelihood ratio test indicated that adding the four interaction terms (Model 5) significantly improved model fit over the model with no interaction terms—Model 3 ($\chi^2 = 33.538$). This indicates that the combined effect of the interaction terms has a statistically significant effect on bank failure rates.

Although comparing the combined effect of interaction terms added to a model represents a standard way to assess an interaction effect, one difficulty associated with this approach is that it is not always possible to distinguish empirically between the various component effects, in part because of a set of highly collinear interaction terms added to the same model. Thus, we also explored the interaction using an alternative approach based on the inclusion of only the variables that significantly contribute to the improvement of model fit (Aiken and West 1991).[9]

To explore the contribution of individual interaction terms, we hierarchically added the all possible combinations of interaction terms between *success experience* and *recovery experience*, starting from only the linear interaction term in Models 4. The results indicated that (1) the linear interaction term (SR) accounted for much of the variance explained by the addition of the bundle of interaction terms, and (2) other interaction terms made very little contribution to the overall model fit. Model 4 that includes only the linear interaction term shows a statistically significant improvement over Model 3, which contains no interaction term. However, adding other three interaction terms—i.e., S^2R, SR^2, and S^2R^2—does not generate statistically significant improvements over Model 4. This supports using coefficients in Model 4 to evaluate the interaction effect. As an additional probe, we used two *information criteria* diagnostics—the Akaike information criterion (AIC) and Bayesian information criterion (BIC)—to explore model parsimony (Cameron and Trivedi 2005). Model 4 in Table 2 has a lower score for both AIC (−341.753) and BIC (−106.415) than Model 5, implying that Model 4 is a more parsimonious model without losing explanatory power, further supporting the use of Model 4 for analysis of interaction effects.

Figure 1 The Interaction Effects Between Success and Recovery Experience on Bank Failure Rates



To help interpret the interaction effect of the success and recovery experience on bank failure rates, we visually depict Mode 4's joint multiplier effects of *success experience* and *recovery experience* in Figure 1.[10] The vertical axis is the natural log of the multiplier of the hazard rate of bank failure, and the horizontal axes represent *success experience* and *recovery experience*, respectively. Figure 1 indicates that the hazard rate of bank failure is lowest when the levels of both *success experience* and *recovery experience* are high, a finding that is consistent with Hypothesis 3. Figure 1 illustrates that the impacts of success and recovery experience are not merely additive, but that the impact of each is enhanced by the presence of the other. The multiplicative interaction effects can be further probed by considering how each type of experience alters the inflection point at which the other type begins to enhance rather than reduce survival. The inflection point of *recovery experience* decreases from 1.00 when firms have no *success experience* to 0.63 when firms are assumed to have a mean level of *success experience* (=0.71). The inflection point of *success experience* decreases from 2.79 in absence of *recovery experience* to 2.40 with the mean level of *recovery experience* of 0.09. In each case, then, the presence of the other type reduces the level of experience needed to produce survival enhancing learning.

As a robustness check, we also created a graph that depicted the joint multiplier effects based on the full model (Model 5), which contains all four combinations of *success experience* and *recovery experience*. This graph provided consistent in-sample predictions with Figure 1.

Discussion

Summary of Findings

In this paper, we theorized that two different types of a firm's own experience influence survival-enhancing learning. We hypothesized that, in the presence of little experience of the same type, success and recovery experience can produce harmful learning outcomes, but that increased levels of the same type of experience will generate useful learning. Furthermore, we argued that each type of experience would enhance the value of the other. Overall, our results are consistent with this contingency model of when and how success and recovery will produce valued learning outcomes. Our framework offers a more complete vision of their learning impact than standard models that imply that more experience leads monotonically and independently to higher learning value.

We proposed that prior experience of the same type will shape each type's impact because—in the absence of prior success or recovery experience—low levels of each will tend to generate harmful learning outcomes. Flawed inferences from a small number of extreme performance outcomes, superstitious learning, and the development of inaccurate models of organizational action will lead to potentially harmful actions and strategies (Argote 1999, Cyert and March 1992, March and Olsen 1976). In addition, the high salience and appeal of these forms of experience (Haunschild and Miner 1997) will exacerbate this danger. Further experience of the same type, however, can overcome these dangers by providing contrasts across different episodes and periods of success or recovery events and by creating a more valid and comprehensive understanding of prior experience, which in turn increases the chances of survival-enhancing action.

The results support this vision of the importance of foundational experience before useful learning can occur. Our results are consistent with prior theory that emphasizes the difficulties and dangers of interpreting low levels of experience and making use of raw experience to guide significant action (March et al. 1991). Our results are also consistent with the construct of absorptive capacity (Cohen and Levinthal 1990)—in which some experience makes possible the interpretation of other experience—and the importance of organizational memory (Moorman and Miner 1997, Walsh and Ungson 1991) in gaining value from new experience. Our results indicate that after a certain level, additional experience can become useful even if the low levels were harmful. In contrast to prior work that found that in some cases experience may have little impact (Van de Ven and Polley 1992), this study explicates and finds evidence for harmful impact of experience. Finally, the pattern of our results contrasts with Baum and Ingram's (1998) finding of a U-shaped relationship between operating experience and firm failure rates in the Manhattan hotel industry. This discrepancy may have arisen from the differences between operating experience and the types of experience we study here. This is an important issue that deserves further attention.

The second theoretical prediction—that the joint presence of both success and recovery experience enhances their separate learning value—was also supported. This is consistent with the emerging emphasis on variability as a source for useful learning in general (Haunschild and Sullivan 2002), but advances it beyond information sources into the realm of direct experience. The combination of success and recovery had more value than either experience alone, which is consistent with inferential learning involving schematic or causal models developed within the organization (March et al. 1991) and the selective retention and elaboration of behaviors from a highly varied pool of actions and outcomes (Levitt and March 1988). The combination of both types of experience offers richer and contrasting experience from which to draw more valid inferences, can help reduce the dangers of potential learning errors and biases, and can provide more complete action templates. Our theoretical approach underscores conditions under which two types of experience should complement rather than substitute for each other's value (Haunschild and Beckman 1998, Schwab 2007).

Our findings, then, support our theoretical framework, which proposes that both success and recovery experience will distinctly affect survival-enhancing learning in firms and that their impacts will depend upon the amount of experience and the presence of each other. Our framework implies that either additional experience of a given type or the presence of the other type can help overcome obstacles to useful learning at low levels of success and recovery experience. Beyond the support for this framework, one other feature of our results seems especially interesting.

Our results also offer interesting insights into the level of success and recovery experience required to generate positive survival-enhancing learning in our sample. First, the presence of each type meaningfully increased the value of the other. As reported, an average amount of success experience reduced the amount of experience needed before which recovery experience enhances survival by 37% (from 1.00 to 0.63). An average level of recovery experience reduced the comparable point for success experience by 14% (from 2.79 to 2.40). Second, although the two variables cannot be directly compared because they are measured in different units, an informal contrast raises the possibility that recovery may be more valuable than success. A discounted sum of approximately three (2.79) success experiences, in contrast to just one discounted sum of recovery experiences (1.00), was required to produce positive survival-enhancing learning. This informal contrast matches arguments that recovery experience provides special value through enhancing both action learning and opportunities for valid inferences (Kim and Miner 2007, March et al. 1991) with less danger of promoting complacency. Further work could usefully test theoretical predictions about what drives the "turning point" beyond which additional units of varied types of experience provide value.

Limitations and Future Research

Our work leaves several key questions for further research. It would be beneficial to study the impact of success and recovery experience in other industry settings, with an eye to identifying scope conditions for the causal factors we developed. In particular, the banking industry is regulated, typically with lower failure rates than some other industries. A future study exploring the impact of these types of experiences in a nonregulated industry and/or high-failure setting would deepen our understanding. Studies in different empirical contexts could also provide further insights on the different findings for the effect of operating experience between this paper and prior work (e.g., Baum and Ingram 1998). One strength of this study is its focus on a cohort of new firms, which allowed us to examine and accurately measure prior success and recovery from the firm's founding. Future research, however, could usefully explore whether the impact of these two of different types of experience will differ in longstanding organizations.

Our theoretical predictions and analyses also involved interactions between variables for which we predicted and found curvilinear effects. This is one of the early studies that explore the interaction effect of two different performance experience *types*, and to our knowledge it is the only one that addresses such curvilinear interactions. Further work could explore other interactions, including both types and levels of organizational experience (e.g., internal experience and external, or industry-level, experience) (Schwab 2007). In the tradition of learning research that looks at long-term learning *outcomes* rather than measuring individual learning processes, this study did not directly measure the behavioral changes or changes in the firms' causal maps, although we did challenge the feasibility of some hypothesized processes in our qualitative work. Continuing fine-grained process research and systematic studies of the microsteps theorized here will have clear value.

In theorizing about the impact of recovery experience, we emphasized two specific aspects: the *transition* from a distress experience to recovery, and the *combination* of contrasting information. Our study opens the door to important additional issues related to recovery. These include the potential impact of the duration of recovery, and of other failure-related experience types such as consecutive performance declines or performance declines that are not associated with a specific performance threshold. On the other hand, we measured success as the accumulated history of high-performance periods, but success can be also measured alternatively. In particular, transition to and from success may produce useful organizational learning just like recovery experience. Future studies that examine different types of success experience will be valuable.

Finally, we examined the impact of success and recovery experience using the survival-enhancing learning framework. Future research on the impact of these experiences on other important organizational outcomes (e.g., growth, search behavior, changes in top executives, or strategic choices such as product mix or mergers and acquisitions) will advance understanding.

Implications for Broader Theory

Theories of Organizational Learning. Our work has important implications for organization learning research more broadly. Our pattern of results reinforces the vision of an ecology of internal organizational experience and learning processes that involves distinct constraints and internal interactions (March 1999a). Recent studies suggest that firms can learn from different types of experience, such as train accidents (Baum and Dahlin 2007), product recall (Haunschild and Rhee 2004), or improvisational activities in product development (Miner et al. 2001). For the most part, each type of learning experience tends to be treated as independent of other types of experience. However, our study theorizes about specific ways that two important types of experience will interact with each other. In our context, the two opposite types of experience interact to mitigate the harmful learning effects that can occur when organizations have only a small sample of such experience. This advances the understanding of ecologies of experience in several ways. First, different types of organizational experience can work through different learning processes (Argote et al. 2003, Schulz 2002). Our arguments posited that firms learn through changes in both activities and in cognitive maps (Gavetti and Levinthal 2000, Miner and Mezias 1996), which highlights these learning channels. Although important simulations have revealed intriguing possibilities for ecologies of learning processes and levels (Lant and Mezias 1992), systematic tests of such interactions within organizations have presented research challenges. Our work proposes and tests a concrete framework for how different types of internal experience interact with each other and shape survival-enhancing learning. Our results indicate a specific pattern for an ecology of internal learning not previously explicated or tested.

In addition, we call attention to a firm's own *recovery experience* as an important potential driver of learning. Although prior work has considered the general idea of rebounding from threats of failure, it has typically focused on the recovery ending itself as the key dependent variable. In contrast, our study systematically tests the impact of the firm's own recovery experiences as an independent variable and the impact of this variable on an organizational outcome—in this case, survival. Kim and Miner (2007) studied industry-level near-failure experience in the banking industry, a construct similar to recovery experience but operationalized *at the industry level*. Their results support their theory that firms can learn vicariously from the industry-level near-failure experience, and our baseline model incorporates their findings. Our paper represents a major advance over this prior work by addressing the impact of internal experience. Taken together, this body of work implies that recovery experiences, whether one's own or others', represent significant drivers of survival-enhancing learning.

Entrepreneurship Research. Because we focus on learning in the presence of little experience of a given type, our theory and results clearly have implications for understanding processes within new firms. Our sample consists of new firms, and our study deepens understanding of the most common type of new firm: those created in an existing industry (Aldrich 2005, p. 469). It advances entrepreneurship research by providing new theory and large-scale empirical evidence on how entrepreneurial firms can learn from their own internal experience after founding.

Researchers have previously emphasized learning by individual founders and founding teams (Aldrich and Ruef 2006, Baker et al. 2002, Minniti and Bygrave 2001, Ruef et al. 2003). They draw on outside experts (Ruef 2002), prior personal experience (Shane 2000), industrywide norms (Klepper 2002), or a parent firm's existing practices (Eisenhardt and Schoonhoven 1990). Other theories emphasize even broader influences such as ethnic communities or national legal structures (Schoonhoven and Romanelli 2001). Our study refocuses attention on a firm's own internal experience after founding, and emphasizes systematic patterns based on internal organization-level experience rather than on individual-level experience (Baker et al. 2002). In short, it concerns organizational entrepreneurial learning. Our theory implies that the pattern of firm-level success- and failure-related experience can affect survival itself, and it suggests that extreme success- and failure-related experiences will have survival value only after an experiential threshold has been achieved. This contrasts with assumptions that a new firm starts with an unconstrained ability to learn and import knowledge. Instead, our framework underscores the criticality of some degree of experience before further experience actually provides value (Gong et al. 2006).

Conclusion

Overall, our theoretical framework and results paint an intriguing portrait of learning related to organizational success and recovery experience. Both forms of experience can produce dysfunctional and useful learning processes, with each having value only after a critical threshold of experience of the same type has been acquired. The two different types of experience can enhance each other's value in survival-enhancing learning, providing another way to overcome dangers of low levels of experience. A new firm's survival is a prerequisite for its own potential growth and helps shape the direction of industry evolution. Our findings, then, open a promising early window into organizational entrepreneurial learning and the broader domain of ecologies of organization-level experience and learning outcomes.

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Endnotes

[1]We thank an anonymous reviewer for these helpful comments and suggestions.

[2]Interview conducted in May 2006. Most interview quotes used in this study were drawn directly from actual quotes with minimum editing. Some interviews were conducted in a foreign language, and were translated into English.

[3]Interview conducted in June 2006.

[4]Interview conducted in December 2005.

[5]The specific details of IDC's form of CAMEL ratings are proprietary but designed to approximate the FDIC CAMEL ratings. The five components of the CAMEL rating are as calculated based on the following: (1) *capital risk* measures credit and interest rate risk, and is determined by Tier 1 capital as a percentage of assets and as a percentage of risk-based assets; (2) *asset quality* is measured by the level of loan delinquency and nonperforming assets relative to loan loss reserves and capital ratios; (3) *margins* measure management's financial controls and are calculated by the spreads between various profitability indices such as interest income and expenses; (4) *earnings* measure the success of the operating strategy and are calculated by the net operating after-tax return on earning assets; and (5) *leverage* measures the efficiency of financial strategy, and is determined by the degree of leverage, the cost of leverage relative to operating returns, and liquidity.

[6]The FDIC CAMEL rating ranges from 1 (highest performance) to 5 (lowest performance).

[7]We thank an anonymous reviewer for the helpful suggestion on the log-transformation of the CAMEL rating.

[8]We estimated models using a density variable that was adjusted by the state-level total gross domestic product to account for the size of each market (i.e., state) and found consistent results.

[9]We thank the senior editor and an anonymous reviewer for helpful comments on different approaches to testing these interaction effects.

[10]The multiplier of the rate represents the risk of experiencing events relative to the baseline hazard. The exponential hazard rate is represented as $r(t) = h_0(t)\exp(\beta x)$, where $h_0(t)$ is the baseline hazard rate and β is a vector of regression coefficients. Because $h_0(t)$ is identical for all variables in the model, the relative effects between predictors can be assessed by comparing the multiplier of the rate, $\exp(\beta x)$, after setting the multiplier to 1 for the baseline hazard rate.

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