

## **The Evolution of Risk and Return in High-Velocity Settings**

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## ABSTRACT

### **The Evolution of Risk and Return in High-Velocity Settings**

Despite much research, debate continues about the impact of risk taking on a firm's future performance. Unlike prior studies, we propose that risk-return relationships evolve as firms age and learn, particularly in high-velocity settings where accumulated knowledge affects how firms respond to technological change. Discerning this requires three things absent from prior analyses: (1) studying an entire population; (2) modeling evolutionary processes; and (3) using separate models to capture how a firm's gains and losses (i.e., its strong and weak performances) unfold across time. Using this framework, we found that (a) risk-return relationships generally evolved from positive to negative as firms aged; because (b) firms learned to avoid large losses at younger ages than they learned to sustain large gains; yet (c) the risk taking that followed below-aspiration performance moderated those effects such that major setbacks prompted large future gains and large future losses among older firms and downward spirals among younger ones.

Relationships between risk and return are central to our lives. In the hope of emotional or monetary rewards, some people take risks by climbing mountains, changing employers, or switching careers. Some executives take risks in pursuit of better pay and enhanced reputations, and some firms pursue risky strategies in a quest for higher sales and profits.

Many studies have considered whether it pays firms to take risks. Some indicate that it does, findings consistent with economic theory, which contends that decision makers demand higher returns in exchange for undertaking projects with greater uncertainty (e.g., Aaker & Jacobson, 1987; Miller & Leiblein, 1996). In contrast, other studies indicate that risk is negatively related to performance (e.g., Miller & Bromiley, 1990). One explanation is that some firms have rare competencies that enable them to perform consistently at a high level (Bowman, 1980). Another, based on prospect theory (Kahneman & Tversky, 1979), suggests that troubled firms take unwise risks on long shots in an attempt to recoup prior losses. As Bromiley (1991: 55) states: “The interesting part of risk seeking by [troubled firms] is not simply that poor performers take more risks, but rather that they take bad gambles – risks with low expected values.”

Despite substantial progress over the past 20 years, much controversy remains about risk-return relationships, which we address by taking a new approach, both theoretically and empirically. To do this, we ask: How do relationships between risk and return evolve across time as organizations age and learn, particularly in high-velocity settings where the knowledge stored in a firm’s routines affects its response to rapid technological change? Our thesis is that prior research has largely overlooked the role of evolution in establishing relationships between risk and return. For instance, prior work has focused almost exclusively on publicly held corporations that are relatively large and old. This ignores the many small and young firms that took risks in an attempt to grow but failed along the way, an omission that creates sample selection and survivor biases (Heckman, 1979). Since firms often fail because they cannot deliver reliable, low-risk performance (Hannan & Freeman, 1984), studies of large and old survivors are incomplete and possibly misleading.

Overcoming such problems requires an evolutionary viewpoint that does not presume that a firm and its environment are stable across time. That assumption underlies virtually all prior work, which has assessed risk and return using the variance and mean of a firm’s performance across multiyear periods. In comparison, an evolutionary perspective suggests that a firm and its

environment may differ greatly between one year and the next. We therefore consider the interaction of two prominent evolutionary forces: (1) path dependencies associated with organizational aging and learning in settings with rapid technological change<sup>1</sup> (Eisenhardt, 1989; Hannan & Carroll, 2000; March, 1991); and (2) sharp alterations to a firm's evolutionary trajectory that occur as it tries to recover from a period of poor performance. Such recovery attempts, which involve substantial risk taking (Greve, 1998; Kahneman & Tversky, 1979), are likely to be frequent in high-velocity industries where even the best-managed firms experience periodic setbacks due to rapid or unexpected shifts in technology and competition.

To develop an evolutionary view of risk and return, we take several steps. First, instead of means and variances calculated across multiyear periods, we focus on *gains* and *losses*, defined as the time-varying magnitudes of above-average and below-average outcomes that a firm is simultaneously exposed to in its next future period. For example, firms undertaking make-or-break projects with promising yet uncertain prospects expose themselves to relatively large future gains and relatively large future losses. That corresponds, qualitatively, to the positive risk-return relationships discussed in prior research. Second, to avoid time-aggregation problems, we consider how gains and losses unfold one-by-one, period-by-period as a firm and its industry evolve. Third, by treating gains and losses as distinct constructs that are analyzed separately, we avoid statistical biases seen in prior work, better represent how managers think about risk, and most importantly, reveal that firms learn to avoid losses much more rapidly than they learn to sustain gains. While our framework differs from earlier research, we show that it maintains strong qualitative similarities. It thus encompasses prior work, yet also extends it by revealing how risk-return relationships evolve.

## **RISK AND RETURN**

This section presents a brief overview of research on risk and return (also, see Ruefli, Collins, & LaCugna, 1999). Economists have long considered how risk affects investors' decisions in securities markets presumed to be in equilibrium (Sharpe, 1964; Lintner, 1965), and strategy researchers have borrowed that thinking and applied it product markets (Bettis & Hall, 1982; Aaker & Jacobson, 1987). While strategists seldom share economists' assumptions about

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<sup>1</sup> We define learning as systematic changes in behavior driven by experience (Miner & Haunschild, 1995). While some forms of learning are adaptive, others are not, including processes that produce superstitious learning and competency traps (Levitt & March, 1988).

rationality and equilibrium, they assume that successful firms are eventually imitated, which lowers their returns, and competition eliminates highly inefficient organizations. Though product markets may not be in equilibrium, they are close enough, some strategists contend, to borrow two ideas from economic theory: (1) managers dislike uncertainty, and (2) competition quickly eliminates opportunities with high prospective returns and low variability. As a result, product markets are argued to rapidly achieve a steady-state in which there is a positive relationship between risk and return, measured by the variance and mean of a firm's performance across time.

While economic thinking pervaded early work, other perspectives emerged after Bowman (1980, 1982) showed that in many industries, the firms with the highest average profits also had the lowest variance. Bowman labeled those negative risk-return linkages a "paradox" because they contradicted economic reasoning. Explanations include (1) some firms have particularly strong managements or competencies that enable them to earn high returns consistently (Bowman, 1982); and (2) managers in low performers take unwise gambles on long shots (Kahneman & Tversky, 1979; Bromiley, 1991). Bowman's findings sparked a wave of inquiry into these ideas.

For our purposes, post-Bowman research can be summarized by its convergence on three themes. First, there is increasing agreement that contrary to economic theory, managers do not universally avoid risk and uncertainty. Instead, as prospect theory argues, their risk preferences are dynamic. Managers whose prior performance exceeded their aspirations become risk-averse and avoid uncertainty, while those who performed below their aspirations become risk-seeking and pursue high-variance investments in hopes of winning big and erasing their losses (Kahneman & Tversky, 1979; Fiegenbaum & Thomas, 1988; Gooding et al., 1996).

A second post-Bowman theme is growing dissatisfaction with using variance to measure risk. Variance-based measures, which include market betas and the mean sum of squared errors around a performance trend line (Wiseman & Bromiley, 1991), confound upside gains and downside losses. Since managers view risk in terms of losses, not uncertainty about potential gains, variance fails to capture how managers think about risk (MacCrimmon & Wehrung, 1986; March & Shapira, 1987; Shapira, 1995). Variance-based measures can also create spurious negative relationships in regression models that predict average performance, particularly if data contain temporal trends (Ruefli, 1990; Wiseman & Bromiley, 1991; Ruefli & Wiggins, 1994). If

firms and industries systematically evolve across time, this threatens the statistical validity of earlier work.

A third theme in the post-Bowman literature has been an increasing call for new methods and measures that move away from the static, equilibrium-based logic inherited from economics and better capture the temporal dynamics inherent in risky situations (e.g., Miller & Bromiley, 1990; Miller & Leiblein, 1996; Wiseman & Catanach, 1997; Ruefli et al., 1999). The following section pursues this suggestion.

To their credit, risk-return scholars have aggressively implemented better theory and methods in the 20 years since Bowman's work. For example, researchers have begun to assess risk in terms of exposures to future losses (McNamara & Bromiley, 1999; Wiseman & Catanach, 1997) and by calculating lower partial moment statistics, which are the probability-weighted magnitudes of performance shortfalls relative to a benchmark (Miller & Leiblein, 1996; Miller & Reuer, 1996). Yet despite these developments, there is still little agreement about whether risk-return relationships are positive or negative, and conflicting results are seen across recent studies (Bromiley, 1991; Miller & Leiblein, 1996) and within those that employ multiple measures of risk (McNamara & Bromiley, 1999; Wiseman & Catanach, 1997).

### **DEVELOPING AN EVOLUTIONARY PERSPECTIVE OF RISK AND RETURN**

We take the conflicting results of past studies as a starting point and propose that there is no universal relationship between risk and return because that association evolves across time. To address this, we identify the features of prior work that have obscured such evolution, and then describe a new framework designed to reveal it.

#### **Fundamental Limitations in Prior Research**

**Sample selection biases.** One reason that prior research has overlooked evolution is that it has focused on publicly held corporations, usually those in the COMPUSTAT or CRSP databases, which contain very large and old firms. Inclusion there requires a listing on the New York or American stock exchanges, so those firms were fairly successful at some point in their history, and their operations and finances were sufficiently documented to be certified by the U.S. Securities & Exchange Commission. As a result, such firms are atypical in their legitimacy, success, access to capital, and the degree to which their internal routines are formalized.

Focusing on such firms produces sample selection biases (Heckman, 1979) because it ignores the fate of the many small and young companies that took risks in trying to become large but failed completely. Such biases may be severe because 50% to 70% of new firms fail within their first 5 years and over 80% in their first decade (Aldrich & Auster, 1986). Including young and small firms in the study of risk and return is vital since they probably exhibit the greatest volatility in their internal routines and performance (Hannan & Freeman, 1984). In addition, they often experiment and take risks because they lack a set of competencies that they can reliably exploit (cf. March, 1991). In comparison, firms in COMPUSTAT or CRSP may often possess such skills, which would account for the negative risk-relationships seen in many studies. Such links may exist, but we doubt that firms become large and publicly traded by playing it safe. Instead, we expect that negative risk-return linkages represent rare outcomes of long evolutionary processes, so it is vital that one's theory and methods accommodate evolution and selection.

**Time-aggregation biases.** A second impediment to capturing evolutionary trends is that prior studies have aggregated across time to derive measures of risk and return. It is very common, for instance, to calculate the mean, variance, or lower partial moment of a firm's performance using annual observations across a five or ten-year window (e.g., Fiegenbaum & Thomas, 1986, 1988; Gooding et al., 1996; Miller & Leiblein, 1996). This assumes long periods of stability, an assumption that is violated if firms or their environments are evolving. When there is evolution, time-aggregation creates two problems: (1) regression models are misspecified because evolutionary variables are omitted, and (2) aggregating across time to calculate mean performance biases standard errors towards zero because it averages away variation in a firm's annual performance (Greene, 1993). Besides creating Type I errors, this magnifies specification biases associated with omitting key predictors (Hannan, Freeman, & Meyer, 1976).

Time-aggregation is also conceptually suspect because there is strong evidence that executives focus on outcomes one at a time; they do not average across them or assess their distributions (MacCrimmon & Wehrung, 1986; March & Shapira, 1987; Kahneman & Lovallo, 1993; Shapira, 1995). Similarly, organizations exhibit sequential attention to goals and problems and generally overlook events or possibilities that are remote in time (Cyert & March, 1963; Levinthal & March, 1993). Thus, while researchers routinely aggregate across time to assess risk and return, managers and organizations do not.

**Biases from aggregating gains and losses.** A final impediment to discerning evolutionary trends is that prior research has aggregated gains and losses. This occurs when regression models estimate average performance across firms (e.g., Bromiley, 1991; Wiseman & Catanach, 1997) or within-firm averages are calculated across multi-year windows (e.g., Miller & Bromiley, 1990; Miller & Leiblein, 1996). Obtaining averages appears sensible, so why not do it? There are both behavioral and mathematical reasons.

Behavioral research indicates that executives often view gains and losses as separate, qualitatively different outcomes, not two subparts of the same one-dimensional scale (MacCrimmon and Wehrung, 1986: 146-147). As an example, Jackson and Dutton (1988) found that possibilities of gains and losses are closely associated with opportunities and threats, which are distinct, independent constructs. Clear threats exist when decision makers may lose but won't gain, and clear opportunities when gains are possible and losses unlikely. Situations are simultaneously viewed as threats *and* opportunities when large gains and losses are both possible. Thus, perceived threat levels may be high or low regardless of opportunities. The two tend not cancel or offset one another in managers' thinking, which suggests that researchers should exercise care before aggregating them.

Simple mathematics also suggests that gains and losses should be separated. Consider a firm that starts with \$100 in shareholder equity at  $t_0$ , pays losses out of that equity and reinvests its profits. Suppose that returns on equity were +50% in  $t_1$  and -50% in  $t_2$ , so its time-series of equity values is \$100, \$150, and \$75. Here, the average return is  $(50\% - 50\%) \div 2 = 0\%$ , so the firm would appear to break even, yet the starting and ending values show an overall return of -25%, a sizable loss. As this illustrates, gains and losses are not mathematically additive due to floor effects. Absolute losses are bounded at 100%, while gains are potentially unlimited, so average return calculations are biased upwards, which can produce misleading estimates of risk-return relationships (Baucus, Golec, & Cooper, 1993).

### **Risk and Return as an Evolutionary Sequence of Gains and Losses**

To address these limitations, we propose a new framework with several unique features. First, to avoid selection biases, we examine an entire population of firms from its very start and carefully consider evolutionary processes. Second, we avoid aggregating across time and consider an unfolding sequence of gains and losses that firms and their executives experience one-by-one.

Third, we treat gains and losses as distinct constructs that are estimated in separate models, which considers both the positive outcomes that a firm might achieve in the future and the downside hazards to which it is simultaneously exposed.

Like others, we are interested in a firm's performance relative to its competitors (Miller & Reuer, 1996), so gains and losses are measured against a competitive benchmark,  $B_t$ , such as the median performance of other firms in the industry in year  $t$ . Gains, then, are the difference between a focal firm's performance and the benchmark for the observations where that quantity is positive, while losses are the absolute value of that difference when it is negative. If the median return on assets (ROA) in an industry was 5%, and firm A had an ROA of 15%, it would contribute an observation to the subpopulation of gains with a magnitude of  $15\% - 5\% = 10\%$ . If the ROA for firm B was 2%, it would contribute an observation to the subpopulation of losses with a magnitude of  $|2\% - 5\%| = 3\%$ .

After separating observations into two separate subpopulations, we then estimate two models that predict, respectively, the magnitudes of future gains and future losses:

$$\text{gain magnitude}_{i,t} \mid y_{i,t} > B_t = y_{i,t} - B_t = \boldsymbol{\beta} \mathbf{x}_{i,t-1} + \boldsymbol{\pi} \boldsymbol{\lambda}_{i,t} + \varepsilon_{i,t} \quad , \quad (1)$$

$$\text{loss magnitude}_{i,t} \mid y_{i,t} \leq B_t = |y_{i,t} - B_t| = \boldsymbol{\gamma} \mathbf{x}_{i,t-1} + \boldsymbol{\theta} \boldsymbol{\lambda}_{i,t} + u_{i,t} \quad . \quad (2)$$

Here,  $y$  is the performance of the  $i^{\text{th}}$  firm in the current period,  $B_t$  is the current-period benchmark,  $\mathbf{x}$  is a vector of predictors measured at  $t-1$ , the  $\boldsymbol{\beta}$  vector captures the effects of those variables on gains, the  $\boldsymbol{\gamma}$  vector does the same for losses, and  $\varepsilon$  and  $u$  are error terms. As detailed later, the  $\boldsymbol{\lambda}$  vector contains selection instruments that account for failure and the probability that a firm will post a gain rather than a loss, and  $\boldsymbol{\pi}$  and  $\boldsymbol{\theta}$  are the associated coefficient vectors.

Because prior research on risk and return has not considered evolutionary processes, our theory and methods differ markedly from it. Rather than replicating earlier work, our goal is to build a qualitative and conceptual bridge between this study and earlier ones so that we can circumvent old roadblocks, yet still draw on the strengths of prior research and communicate in the field's customary language. Our definitions of future losses and gains allow us to do this because they are quite similar to the qualitative meanings of risk and return contained in earlier work. The following section develops this further.

**Bridging to prior research.** To grasp the qualitative similarities between prior research and the framework described here, it is important to note that equations 1 and 2 involve

simultaneous conditional means. We do not know at time  $t-1$  whether a firm will experience a gain or a loss in the following period, but we can obtain parameter estimates ( $\beta$  and  $\gamma$ ) that tell us the magnitudes of gains and losses that a firm is simultaneously exposed in its future. From this, we can infer what the size of a future loss is likely to be – conditional on its occurrence, and what the size of a future gain is likely to be – conditional on its occurrence. Suppose, for instance, that  $x_1$  measured R&D spending and analysis revealed that  $\beta_1 > 0$ , and  $\gamma_1 > 0$ . If so, firms that spent heavily on R&D today would have particularly large future gains *and* particularly large future losses, yielding both big winners and big losers. More generally, equations 1 and 2 allow a variable  $x_i$  to have a negative, null, or positive relationship with future gains, and a negative, null, or positive relationship with future losses. This leads to the nine possibilities summarized in the matrix shown in Figure 1.

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 Insert Figure 1 about here  
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As Figure 1 suggests, our framework shares qualitative similarities with the major theories of risk and return. Cells 1 and 9 in Figure 1’s northwest and southeast corners are similar to an economic perspective in which competition coupled with decision makers who dislike uncertainty create positive risk-return relationships. Forces in cell 1 decrease future gains and losses ( $\beta_i < 0$ ,  $\gamma_i < 0$ ), which would be preferred by those willing to trade upside potential for greater certainty. And cell 9, where our hypothetical example for R&D spending would fall, is occupied by forces that increase future gains and losses ( $\beta_i > 0$ ,  $\gamma_i > 0$ ), which would be preferred by those who willing to tolerate greater uncertainty in exchange for greater upside potential.

In contrast, cells 3 and 7 in the northeast and southwest corners correspond with the Bowman paradox in which there is a negative link between risk and return. Factors in cell 3, such as distinctive competencies, may enable some firms to enjoy above-average gains with little exposure to losses. Factors in cell 7, such as unwise gambling by troubled firms, would do the opposite, increasing losses and decreasing gains. Prospect theory would also appear to fall in cells 3 and 7 because it predicts negative risk-return linkages. However, since its proponents focus on bad gambles by troubled firms (cell 7), forces in cell 3 that produce small future losses and large future gains are not considered. Strong and consistent performance by some firms is an alternative explanation for negative risk-return associations, and one that is distinct from

gambling, so applying prospect to theory to risk and return may create a conceptual and empirical confound. In comparison, our framework can determine if gambling (cell 7), rare skills (cell 3), or both lead to negative risk-return relationships.

This framework has other advantages. First, it does not aggregate gains and losses, nor does it aggregate across time, so the biases discussed earlier. Second, it identifies combinations of gains and losses in cells 2, 4, 6, and 8 that prior theory does not contemplate. Space constraints prevent extensive coverage, but one example is cell 2, which is populated by forces that decrease future losses yet have no effect on future gains. Here, we borrow from Herzberg (1966) and refer to those as hygiene factors because they mitigate poor results yet have little power to effect good ones. Third, our framework accords with behavioral research, which indicates that managers view risk as their exposure to future losses, not uncertainty about future gains.

## **Hypotheses**

In this section, we consider how risk-return relationships, as revealed by patterns of gains and losses, change across time as firms evolve from entrepreneurial startups into more mature organizations. We are particularly interested in how this process unfolds in high-velocity industries in which changes in technology and competition are rapid, ongoing, and often unpredictable. We expect that almost all firms in a high-velocity industry, even the best-managed ones, will experience occasional stumbles and setbacks. As prospect theory details, firms typically respond to periods of poor performance by taking greater risks (Tversky & Kahneman, 1979), and we are interested in how the returns to such endeavors evolve across time. Consequently, we consider how the interaction of a firm's age and its response to a period of poor performance affects the magnitudes of future gains and losses. We turn first to the intrinsic shapes that gain and loss curves are likely to exhibit with respect to age.

Ecology and learning theory both argue that performance variability decreases over time because experience allows a firm to better define its roles, build trust among its stakeholders, and embed its actions in a set of reliable and reproducible routines (Hannan & Freeman, 1984; Carroll & Hannan, 2000). Since routines are rooted in the firm as a whole, their evolution is clocked by the organizational aging process, and while young firms often experiment and take risks, such exploration is gradually driven out by exploitation, which entails incremental refinement and uncertainty reduction (Levinthal & March, 1993; March, 1991). Firms therefore exhibit a bias

towards exploitation (Baum & Ingram, 1998), a trend of decreasing variability that is consistent with the satisficing principal wherein firms seize on and refine solutions in the near neighborhood of the status quo (Cyert & March, 1963).

Technological innovations in high-velocity settings give birth to many new niches and sub-fields (Florida & Kenney, 1990). And because startups are less inertial than older firms (Hannan & Freeman, 1984), some will seize favorable positions in emerging niches and post strong gains, at least for a time. But while some will initially prosper, new organizations are subject to many hazards because they lack legitimacy and well-rehearsed skills (Hannan & Carroll, 2000). Many other young firms will thus perform poorly, resulting in wide variation across startups. Ecology and learning theory therefore conclude that performance variability will begin at high levels and then decrease as firms age.

While we agree that variability – and hence, the magnitudes of gains and losses – will initially decrease after founding, we theorize that a different pattern will soon emerge because firms learn to avoid below-average outcomes more rapidly than they learn to sustain above-average results. The first portion of this two-part story is that poor performance can be overcome by adopting professional business practices, such as internal cost accounting, that are broadly diffused and well documented. Though widespread among large and old firms, such practices are not universal, especially among the very young, because entrepreneurs resist formalism, and executing such routines requires some learning by doing.

While adopting professional practices will not produce above-average performance, it will mitigate particularly poor outcomes. As an example, prior research indicates most young firms do not have formal human resource management (HRM) departments, and accordingly, only a small minority have formal systems to compensate their managers and employees on the basis of firm performance, which might be done through stock option plans, profit sharing, or plans that tie bonuses to firm-level results (Snell, 1992; Welbourne & Andrews, 1996). While formal HRM and pay-for-performance plans are ubiquitous among established organizations, they are rare among young firms despite strong empirical evidence that they sharply reduce the odds that startups will perform poorly (Welbourne & Andrews, 1996). While formal pay-for-performance systems are unlikely to produce above-average results, they encourage the structural cohesion that young firms

need to avoid particularly bad outcomes. This suggests that the forces that affect the evolution of losses may be quite different than those that drive gains.

While the ability to avoid losses develops fairly quickly because young firms can imitate widespread and well-documented practices, the ability to sustain above-average performance develops more slowly, which is the second part of this story. Sustaining above-average results requires rare, firm-specific capabilities whose assembly involves path-dependent, trial-and-error learning that is not readily transferable across organizations (Barney, 1991; Peteraf, 1993). Thus, widely diffused professional practices, such as formal compensation plans, serve as hygiene factors that decrease the odds of poor performance, yet they seldom produce above-average outcomes, which require idiosyncratic, firm-specific expertise. As Simon (1991) details, true expertise arises slowly because it requires knowledge of thousands of facts and a commensurate number of connections among them. Research shows that “no one – literally no one – becomes a world class expert in any professional domain with less than ten years of full-time dedication to learning” (p. 129). Firm-level expertise is also likely to develop slowly since rare and difficult-to-imitate capabilities tend to arise from highly complex social systems (e.g., 3M’s innovative culture, or Toyota’s lean production system) or path-dependent skills that require substantial time to form (Dierickx & Cool, 1989; Barney, 1991; Peteraf, 1993).

If difficult-to-imitate capabilities arise slowly, then gains will have a U-shaped relationship with age, becoming smaller as young firms with favorable market positions are gradually imitated, but eventually increasing as highly experienced firms develop rare forms of path-dependent expertise. Some startups, particularly in high-velocity settings, will initially post gains due to their nimbleness in entering emerging subfields, but they will lack the skills to sustain their advantages. Since sustainable advantage in the form of increasing gains with age requires time to develop, gains will decrease at first, then gradually rise at higher ages. In contrast, the magnitudes of future losses will decrease not only among younger organizations, who reduce them by adopting professional business practices, but also among older firms, who further reduce them by developing rare skills that provide a partial shield against competition.

Overall, a U-shaped relationship between gains and age, coupled with a negative relationship between losses and age, places younger firms in cell 1 of Figure 1 and older organizations in cell 3. Younger organizations will therefore exhibit positive risk-return

associations because smaller opportunities for future gains are offset by diminished exposures to future losses. In contrast, older firms exhibit negative risk-return relationships because they enjoy opportunities for large future gains with small exposures to future losses.

**Hypothesis 1a:** Future gains will have a U-shaped relationship with firm age.

**Hypothesis 1b:** Future loss magnitudes will have a negative relationship with firm age.

Though aging clearly affects learning, it might appear out of place in a risk-return study since managers cannot choose how old their firms are. Though age is not a choice, it does tell us a great deal about the accumulation of choices and decisions, both conscious and unconscious, that a firm's managers have made across time. In discussing, for example, how young firms gradually adopt professional business practices, we are referring to choices and decisions that managers make as they attempt to establish control over unruly startups. That process reflects both entrepreneurs' desires to bring order out of chaos, and the normative pressures that managers perceive and gradually act upon (DiMaggio & Powell, 1983). Therefore, aging and managerial choices about risk and uncertainty are tightly interwoven.

Regarding our next prediction, we note that the trajectories in hypotheses 1a and 1b are part of a richer story since how a firm reacts to a poor performance moderates the aging process. We contend that high-velocity environments produce an unfolding set of technological jolts and competitive shocks that are likely to cause even the best organizations to occasionally stumble. So even if losses decrease with age as H1b predicts, many firms will still experience sizeable setbacks from time to time. Such losses are integral to risk and return because prospect theory (Kahneman & Tversky, 1979) and organizational learning theory (Levinthal & March, 1981) indicate that firms often take risks when their performance falls below their aspiration level.

Though empirical work consistently shows that below-aspiration results beget future risk taking, it is unclear how that affects future performance. Bromiley (1991) found that the risk taking prompted by poor results decreased future performance, yet Miller and Leiblein (1996) found the opposite, and Greve (1998, 1999) found that such risk taking produced regression to the mean. These conflicting results, we believe, may exist because prior studies have not considered how a firm's ability to take informed risks after a set of bad outcomes interacts with the aging process, particularly in high-velocity settings.

While we agree that weak performance creates pressures to take risks, such forces are not unfamiliar in high-velocity settings where firms are constantly threatened by technological change, and those that do not make a habit of betting on unproven ideas quickly become obsolete. High-velocity environments and instances of poor performance are therefore similar because both create salient threats that promote risk taking. And since threats evoke well-rehearsed responses that reflect the learning embedded in a firm's routines (Staw, Sandelands, & Dutton, 1981), organizations in fast-paced environments are likely to react to poor performance by exercising the same routines that they use to address rapid external change.

As firms age in a dynamic setting, then, what do they store in their routines that conditions their response to below-aspiration performance? We believe that while aging induces adaptive learning in some firms, it leads to superstitious learning in others, and that disparity becomes apparent among organizations attempting to recover from poor performances. The first half of this argument draws on research on dynamic capabilities, which suggests that some firms develop routines that enable them to quickly adapt to changing conditions. Such capabilities may reside, for example, in routines for new product development, processes within top management teams for making fast strategic decisions, or the scripted steps that serial acquirers take to quickly integrate new knowledge (Eisenhardt & Martin, 2000; Karim & Mitchell, 2000; Teece, Pisano, & Shuen, 1997). While there are many types of dynamic capabilities, most are based on organizational routines that develop gradually across time through path-dependent, experiential learning (Eisenhardt & Martin, 2000; Helfat & Raubitschek, 2000).

If some firms gradually develop dynamic capabilities as they age, they will respond to below-aspiration performance by aggressively exercising their core routines, and those responses will often be adaptive. Such firms will undertake riskier changes than they would if their recent performance were better, but that will frequently result in strong future gains because the routines they invoke will contain substantial knowledge about how to manage change. If greater shortfalls relative to one's aspirations evoke more forceful responses (Kahneman & Tversky, 1979), then:

**Hypothesis 2a:** The interaction of firm age and the degree to which a firm's prior performance falls short of its aspirations will be positively associated with the magnitude of future gains.

Dynamic capability formation portrays the optimistic side of aging, but there is a darker one as well. In fast-paced settings, environmental feedback is noisy and confusing, and cause-and-

effect relationships are difficult to discern (Levinthal & March, 1993; Lounamaa & March, 1987). The data that a firm interprets as it tries to understand how its actions affect performance is thus confounded with ongoing technological changes and the simultaneous actions of a shifting set of competitors. One way to handle this is to act quickly and learn fast on the basis of minimal data, yet that carries its own risks. As Levinthal and March (1981: 323) observe: “Fast learners adapt quickly to correct signals; [but] they also adapt quickly to false signals”. Because of this, we argue that the causal ambiguity that pervades high-velocity settings makes them a prime location for superstitious learning (cf. Levitt & March, 1988) in which firms misinterpret their historical experiences and misconstrue causal relationships.

As firms age, the gap between those who have actually developed dynamic capabilities and those who superstitiously believe that they can manage change is likely to widen. Following poor performance, when the pressure to take risks and make changes is high, some firms, as hypothesis 2a predicts, will respond adaptively. Others, though, will place bets and invoke routines that are built on false lessons and dubious conclusions. Consequently:

**Hypothesis 2b:** The interaction of firm age and the degree to which a firm’s prior performance falls short of its aspirations will be positively associated with the magnitude of future losses.

Together, H2a and H2b indicate that the future is highly uncertain for older firms that take aggressive risks after failing to meet their aspirations. Some will recover and post large gains, but others will continue their downward spiral. More broadly, we have hypothesized that (i) future gains will have a U-shaped relationship with age, and gains will be particularly large among older firms that have performed below aspirations; and (ii) future losses will generally decrease with age, but less so among older firms that have underperformed. Indeed, if the positive effect of the age x underperformance interaction in H2b is strong enough, it may reverse the general decline in loss magnitudes that H1b predicts. Thus, a sudden jolt that produces a large loss in an older firm may shift its future risk-return relationship from negative (increasing gains, decreasing losses) to positive (increasing gains, increasing losses).

## METHODOLOGY

To test our ideas, we studied the population of firms in the U.S. personal computer industry, a high-velocity setting (Eisenhardt, 1989), from its founding in 1975 through 1994. That population includes manufacturers of microcomputers (e.g., the Apple Macintosh) and desktop

and desk-side personal workstations (e.g., Sun Microsystems' SPARCstation). We drew data from a census listing, purchased from the International Data Corporation (IDC), of all domestic firms and foreign subsidiaries that built such computers in the United States. The IDC listings were updated annually and provide dollar sales and technical information on all models of personal computers that were introduced during that time. From 1975-1994, 736 firms entered the industry and 576 failed. There were 3,445 firm-years of data.

### **Dependent Variables**

Our dependent variables were conditional gains and losses in performance relative to other firms in the industry. Deriving those measures involves selecting a performance metric and establishing a benchmark that separates gains and losses. Here, performance was measured by sales growth, a variable often used by strategy researchers (see Capon, Farley, & Hoenig, 1990), and in this industry, a strong indicator of a firm's economic and technical viability (Henderson, 1999). Prior work on risk and return has typically assessed performance using profit measures such as return on assets. Here, the vast majority of firms were private, so that data was unavailable, yet three things suggest that was not a concern.

One, in a meta-analysis of 88 empirical studies, Capon et al. (1990) found that sales growth was strongly, positively, and significantly related to profitability. Two, business and trade press articles consistently indicate that the PC firms with strong profits and stock prices were those that grew their sales faster than the industry. Three, managers and investors strongly desire sales growth. Managers do because their power, prestige, and pay are closely tied to firm sales (e.g., Finkelstein & Hambrick, 1988). Investors also value growth in high-tech firms because it signals technological strength and future earnings potential (Florida & Kenney, 1990). Thus, sales growth is an important performance measure here, and many managers will take risks to achieve it.

Given this, we calculated the fractional increase in a firm's deflated personal computer sales from the prior to the current year:  $\text{sales growth}_t = (\text{sales}_t - \text{sales}_{t-1}) \div \text{sales}_{t-1}$ . As a competitive benchmark, we then assessed industry growth over the same period, excluding the focal firm:

$$B_{i,t} = (\sum_{j \neq i} \text{sales}_{j,t} - \sum_{k \neq i} \text{sales}_{k,t-1}) \div \sum_{k \neq i} \text{sales}_{k,t-1}$$

Here,  $i$  identifies the focal firm,  $j$  indexes all firms in the industry for year  $t$ , and  $k$  does the same for year  $t-1$ . Finally, we calculated the conditional gain or loss for the  $i^{\text{th}}$  firm in year  $t$ :

$$\text{gain magnitude}_{i,t} = \text{sales growth}_{i,t} - B_{i,t} \text{ for } \text{sales growth}_{i,t} > B_{i,t}, \text{ and missing otherwise;}$$

loss magnitude<sub>i,t</sub> = |sales growth<sub>i,t</sub> - B<sub>i,t</sub>| for sales growth<sub>i,t</sub> ≤ B<sub>i,t</sub>, and missing otherwise. This produces two subsamples, one of gains, the other of losses, and a given observation will appear in exactly one and be recorded as missing in the other. As detailed later, these subpopulations were analyzed in separate models.

Note three features of those measures. First, the benchmark for assessing gains and losses (B<sub>i,t</sub>) uses the industry as a whole rather than average or median growth levels. As discussed earlier, averaging gains and losses is misleading because losses exhibit floor effects. Also, growth involves year-to-year calculations, so averages or medians would inappropriately exclude two sets of firms: (a) those with sales in year t-1 that failed before year t, and (b) new entrants in year t, which did not exist in year t-1.

A second point is that gains and losses are difference scores, which have been criticized for having low reliability (Cronbach & Furby, 1970). Allison (1990), however, demonstrates that is not the case, and in fact, differencing reduces specification errors arising from unobserved industry features. Third, acquisitions affect sales, but they were rare in this industry, and when they occurred, operations were not meaningfully combined (Ingram, 1993). For instance, when AT&T acquired NCR in 1991, their legal ownership was merged but their operations remained separate. In the 8 cases where acquisitions took place, we treated them as the ongoing operation of distinct entities. Dropping the post-acquisition observations did not alter the results.

Plots of the distributions of gains and losses indicated that gain values were considerably skewed to the right, so the natural log of (1+gain<sub>i,t</sub>) was analyzed. The lag structure of equations 1 and 2 causes observations from the first year of a firm's life to be lost, so there were 1,284 observations in the subpopulation of gains, and 1,425 losses.

### **Independent Variables**

The hypotheses consider the interaction of firm age and the degree to which a firm's prior performance fell short of its aspirations. *Firm age* was measured by the number of years that an organization had participated in the personal computer industry. We also calculated the square of age to detect curvilinear relationships. Both values were measured at time t-1.

To capture how much risk a firm is likely to take after it performs poorly, we drew on Greve's (1998) recent study of prospect theory, which indicates that firms behave quite differently depending on whether their prior performance exceeded or fell below an aspirational reference

point. As Greve showed, such effects can be modeled using a spline function in which separate variables are coded for performance above and below a historical or socially-based target. We found that measures based on those two targets were highly correlated ( $r > .90$ ) and yielded the same results. Social measures are reported below and equaled the fractional change in sales between t-2 and t-1 for the focal firm minus the corresponding value for the entire industry excluding the focal firm<sup>2</sup>.  $Performance < aspirations_{i,t-1}$  equaled the absolute value of that difference when it was negative and 0 otherwise.  $Performance > aspirations_{i,t-1}$  equaled that difference when it was positive and 0 otherwise.

### Control Variables

**Organizational controls.** We controlled for several firm-level factors. Unless noted, all were lagged by one year and updated annually. *Firm size* taps into the formalism of a firm's routines, its economies of scale, and its level of slack, which influences risk taking. We measured this by calculating the log of firm sales in year t-1, which points to its scale of operations and amount of financial slack. Its square was not significant (cf. Haveman, 1993). As an indicator of how diversified a firm was, we counted the number of *current products* listed in the IDC database that non-zero sales in a focal year. The number of *new products*, which taps into risk taking, was derived from the product introduction dates in the data. We also coded a dummy variable to distinguish between *de novo* entrants, which are startups, and *de alio* firms, which entered the industry by diversifying from another business. *De alio* firms have greater access to resources, and their corporate parents often impose formal controls that may affect variability (Carroll et al., 1996). This control was not time-varying.

Some personal computer firms changed technology strategies, which can affect performance (Amburgey et al., 1993). In this industry, proprietary strategists developed their key technologies internally and emphasized performance and specialized features, while standards-based strategists used technologies that conformed to publicly available specifications and emphasized price and compatibility (Henderson, 1999). Apple is an example of a proprietary strategist; Compaq and

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<sup>2</sup> This two-year lag would have produced missing values for all two-year old firms, which formed 19.4% and 18.5% of the gain and loss samples respectively. To avoid this, we took their sales at t-1 (when they were one-year old), divided it by the average sales of all other one-year olds in the same year, then subtracted 1. If, for instance, a firm exceeded the first-year average in year t by 15%, this produced a value of 0.15, which was then benchmarked against industry growth in that year.

Gateway are standards-based. To model strategy changes, which 12% of the firms undertook, products were deemed standards-based if they conformed with one of the three publicly available specifications that emerged in the industry. Those were products with microprocessors that were Zilog Z80-compatible, Intel x86-compatible, or Sparc-compatible. All others were designated proprietary. Next, the *technology strategy* dummy was coded 1 if a firm derived over 50% of its annual sales from proprietary products and 0 otherwise. *Changed strategy* was coded 1 beginning in the year that a firm's sales switched to or from a proprietary majority. Once set at 1, it retained that value, and it was coded 0 otherwise. To assess the dynamics of change, *change clock* (Amburgey et al., 1993) was initially set to 0, and in firms that switched strategies, it recorded the elapsed years since the switch to or from a proprietary majority.

**Environmental controls.** We also controlled for several factors that affect competition and resource munificence. *Population density* affects levels of competition and social legitimation (Hannan & Carroll, 1992), so it was measured by counting the number of living firms in each year. Where it was significant,  $\text{density}^2/1000$  was also included. *Founding density* can have long-lasting performance effects (Hannan & Carroll, 1992), so it equaled the number of living firms in the year that a focal firm commenced sales. It was not time-varying. To account for the size of the resource space, we calculated *total industry sales*, which was the natural log of annual PC sales by all firms. Also, the widespread adoption of IBM-compatible products suggests that network externalities may have been present, which exist when one customer benefits from purchases of compatible products by others (Katz & Shapiro, 1985). We therefore measured the *IBM installed base* by the natural log of the cumulative number of IBM-compatible systems that had been sold in the industry (Henderson, 1999).

Firms using similar technologies often form communities whose members compete with one another yet also share infrastructure and legitimacy (Baum & Oliver, 1992; Wade, 1996). Henderson (1999) listed 55 technical communities in this industry for the period 1975-1992. We used that list and identified 33 more that emerged during 1993 and 1994, then coded several variables. *Community size*, which signals system-level economies of scale, was measured by taking the natural log of the total annual sales of PCs in each community. A community's age may affect its legitimacy and the datedness of its technology, so *community age* was measured in years. The number of firms in a community may affect competition and legitimation, so

*community density* was controlled. For the firms that were members of multiple communities, we weighted these measures by the number of products a firm had in each of its several communities in a given year. Finally, community sponsors invite second source entry by licensing their product designs and may enjoy certain advantages (Wade, 1996). Proprietary strategists did not license their designs, but IBM and Sun Microsystems did, so *community sponsor* was coded 1 for IBM starting in 1981 (the year it began licensing the PC) and for Sun Microsystems starting in 1989 (the year began licensing its Sparc technology). That variable was coded 0 otherwise.

**Control for failure-based selection.** As firms age, some fail and exit the population, which may create sample selection bias. To correct for this, we used a two-step procedure (Heckman, 1979; Lee, 1983). First, we estimated an event history model with an exponential distribution using lagged values of the predictors to obtain  $F(i,t)$ , the cumulative probability density function for the  $i^{\text{th}}$  firm at time  $t$ . This was done on the full population with failures coded as events that occurred halfway through year  $t$  (Peterson, 1991), and years in which a firm survived coded as right-censored. Second, we used the estimated values of  $F(i,t)$  and Lee's formula to obtain  $\lambda_{i,t}$ , the estimated likelihood that firm  $i$  would fail in year  $t$ .

### **Modeling and Estimation**

Analyzing subpopulations of gains and losses differs in several ways from typical performance modeling. Gains and losses have truncated, non-normal distributions because observations are non-missing only when they fall above (or below) a threshold. Truncation also shifts the mean, restricts variance, and it can create selection bias because the factors that affect the sizes of gains and losses may also affect their probabilities. The following discussion, which draws heavily on Greene (1993: 682-714), describes how we handled this for gains. Losses were estimated separately following the same steps.

To correct any selection biases, we used a Heckman-style procedure. First, a discrete-time event history model with lagged values of the predictors estimated the probability that an observation would yield a gain in the following year:

$$\text{Gain probability}_{i,t} = \frac{\exp(\boldsymbol{\pi} \mathbf{x}_{i,t-1})}{[1 + \exp(\boldsymbol{\pi} \mathbf{x}_{i,t-1})]} \quad . \quad (3)$$

Here,  $\mathbf{x}$  is the vector of predictors, and  $\boldsymbol{\pi}$  contains the coefficients from the event history model.

We then controlled for that probability in the gain analyses. In the event history model, we used a logistic function since the sales totals that determined gains and losses were tallied at the end of

each calendar year, a true discrete event (Allison, 1995). In other models not shown here, we interacted gain probabilities with the other predictors to further assess sample selectivity (Greve, 1999). Those interactions were not significant, and the other results were unchanged. Note that sample splitting does not waste information because all data are analyzed across the gain and loss models. Instead, sample splitting acknowledges that two different regression coefficients are needed ( $\beta$  and  $\gamma$ ) to fully describe the effects of a given predictor<sup>3</sup>.

OLS and GLS estimates are biased, inefficient, and heteroscedastic when applied to non-normal distributions that are restricted to positive values (Greene, 1993), so gains were assessed using generalized estimating equations (GEEs), which rely on maximum likelihood. GEEs are an extension of the family of generalized linear models that are particularly useful for analyzing longitudinal data with non-normal distributions (Liang & Zeger, 1986; Lipsitz et al., 1994). They have 4 parts: (1) a linear component,  $\eta_i = \beta x_i$ ; (2) a link function,  $g$ , which may be nonlinear, that describes how the means of observed values are related to the linear component:  $g(\mu_i) = \eta_i = \beta x_i$ ; (3) a specification of the distribution from which  $\mu_i$  is drawn; and (4) a specification of the correlation structure (e.g., autoregressive) among time-series outcomes.

Gain and loss distributions had modes close to the origin and long tails to the right, so we used gamma-distributed GEE models with log link functions (SAS Institute, 1997) and a first-order autoregressive correlation structure. Results were unchanged with random effects models. The GEE models also corrected for under- and overdispersion and provided robust variance estimates (White, 1980) that account for heteroscedasticity and unobserved differences across firms. We did not use fixed-effects models because the within-firm mean deviations would have caused about half of a firm's observations to be gains and half to be losses, regardless of its relative performance standing.

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<sup>3</sup> Instead of splitting gains and losses into separate subsamples, we might have assigned losses a value of zero in the gain analyses then estimated tobit models to deal with the resulting truncation (Greene, 1993). We rejected that approach, however, because it violates a critical assumption of tobit analysis, which is that a variable's effect on the probability of a non-zero outcome must have the same sign as its effect of the magnitude of non-zero outcomes (Greene, 1993: 700). That would not be true if risk-return relationships were positive. For instance, R&D spending might yield large gains if things turned out well, yet also increase the odds of write-offs and losses. In that case, R&D would increase gain magnitudes and decrease gain probabilities, which tobit analysis cannot handle.

## RESULTS

Table 1 gives descriptive statistics for the key variables. Some controls were substantially correlated, so we assessed collinearity using condition indices (Belsley, 1991). The only problematic overlap was between community size and community density, and since the former was not significant, it was pruned from the models reported below.

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Insert Table 1 about here  
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**Gain and loss models.** Tables 2 and 3 report results of the gain and loss analyses. The first model in each table (1 and 5, respectively) contains the controls. The next model (2 and 6) adds the independent variables. Age<sup>2</sup> was significant for gains, but not for losses. The next model (3 and 7) adds the interactions and shows that age x performance > aspirations was not significant ( $p > .71$  for gains;  $p > .87$  for losses), so we dropped that term from models 4 and 8 to reduce collinearity. Fit was assessed by multiplying each model's log likelihood score by -2, which yields a chi-squared distributed statistic. In analyses not shown here, we interacted the aspiration splines with age<sup>2</sup>. Those terms were not significant, and the other results were unchanged, so we used models 4 and 8 to assess the predictions.

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Insert Tables 2 and 3 about here  
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In Table 2, the negative effect of age and the positive one for age<sup>2</sup> supported hypothesis 1a, which predicted a U-shaped relationship between age and future gains. As hypothesis 2a predicted, the interaction of age and performance < aspirations was positive and significant, so the risk taking that followed large losses produced strong gains among older firms. In Table 3, the negative effect of age on future losses supported hypothesis 1b. And the positive effect of age x prior performance < aspirations supported hypothesis 2b, so the risk taking that followed below-aspiration outcomes increased the size of future losses among older firms.

**Interpretation.** To better interpret the results, Figures 2 and 3 graph the interactive effects of age and prior performance < aspirations on future gains and losses. Each graph contains curves that correspond to three values of the below-aspiration spline: (1) its mean plus one standard deviation, a poor prior outcome; (2) its mean, signaling a moderate prior loss; and (3) zero, for firms that had exceeded aspirations. Since the GEE models have a log link function, each variable contributes multiplicatively to an overall effect:  $\exp(\beta_1 x_1) * \exp(\beta_2 x_2) * \text{etc.}$  The vertical axes

thus show multipliers, and 1.0 represents an average gain. Figure 2's top curve reveals that among firms who performed poorly last year, future gains were 1.30 times average at age 2; they dropped to 0.97 times average at age 9, then increased to 2.67 times average at age 20. Figure 5 shows that future losses decreased with age for firms that had exceeded aspirations or missed them by a moderate amount. In contrast, firms that performed poorly in the past saw their future losses increase until they were 1.97 times average at age 20.

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Insert Figures 2 and 3 about here  
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We can look across Figures 2 and 3 and map the results back to Figure 1, which showed the qualitative links between our framework and prior research. Firms who previously exceeded their aspirations or missed them by a moderate amount (the bottom two lines in each graph), evolved from the positive risk-return linkage in cell 1 of Figure 1 (decreasing gains, decreasing losses) to the negative association in cell 3 (increasing gains, decreasing losses). Startups therefore exhibited wide variability in their performance, which gradually narrowed for about a decade. Losses for such firms began decreasing from birth, while firms initially posting strong gains were unable to preserve them. Sustained, above-average performance, which accords with the beneficent part of the Bowman paradox, only emerged after a decade of cumulative learning.

The second point that these graphs make is that prior performance well below a firm's aspirations (the top line in each graph) caused risk-return relationships to change signs. If a young firm was evolving along the bottom line in each graph but then performed poorly and took large risks, it shifted from cell 1 (decreasing gains, decreasing losses) to cell 7 (decreasing gains, increasing losses) where gambling by troubled firms led to downward spirals. In comparison, if an older firm was evolving along one of the bottom two lines but then experienced a large setback, it shifted from cell 3 (increasing gains, decreasing losses) to cell 9 (increasing gains, increasing losses), so its future performance became particularly uncertain. The discussion section further addresses such shifts.

**Robustness.** In other models not reported here, we assessed the robustness of our results by including controls for population mass (Barnett & Amburgey, 1990), size-localized competition (Hannan, Ranger-Moore, and Banaszak-Holl, 1990), prior foundings and failures (Delacroix, Swaminathan, & Solt, 1989), the sum of ages of all living organizations (Barnett, 1997), and first-

mover effects relative to the introduction of new generations of microprocessors (Lawless & Anderson, 1996). Those effects were not significant and the other results were unchanged. We also interacted population density with population age. Again, results were robust. Finally, we assessed partial adjustment models with non-linear least-square estimators (Greve, 1999), with gains and losses estimated separately. Those results were also unchanged.

## DISCUSSION

We have proposed that risk-return relationships evolve across time, so prior research on large, old, and relatively successful firms is incomplete and possibly misleading. Our results strongly support that thesis since risk-return relationships, as indicated by the magnitudes of future gains and losses, exhibited major shifts as firms aged. The four corner cells of Figure 1 map the existing theories of risk and return onto our framework. Cells 1 and 9 on the northwest-southeast diagonal correspond to the positive risk-return linkages discussed in economics, which arise when decision makers make tradeoffs between the magnitudes of potential gains and losses. In comparison, cells 3 and 7 on the northeast-southwest diagonal correspond to negative risk-return relationships in which troubled firms make bad gambles (cell 7), or selected firms with rare competencies enjoy large gains with little exposure to large losses (cell 3).

Our results indicate that a firm might visit each of those four cells as it aged and tried to cope with the jolts and shocks that characterize high-velocity environments. Young firms, those less than 11 years old, bounced between cells 1 and 7 on the left side of the matrix depending on their prior performance. In cell 1 were untroubled young organizations, those that previously exceeded their aspirations or missed them by only a moderate amount, who saw their future gains and losses decrease with age. That reflected increasing reliability and formalism in their routines (Carroll & Hannan, 2000; March, 1991) and reactions by competitors who gradually imitated startups that had initially prospered by entering emerging niches and subfields.

In cell 7, we found troubled young organizations who had substantially underperformed their aspirations. As they aged, those firms exhibited decreasing future gains and increasing future losses, suggesting that after bad outcomes, they often made ill-conceived bets on long shots that seldom paid off (cf. Bromiley, 1991). Since those penalties worsened across the first decade of a firm's life, the troubled young were likely to enter downward spirals in which poor performance prompted unwise gambling, which further decreased future performance and led to

even more desperate risk taking (cf. Bowman, 1982). The inability of the young to bounce back from losses and convert their aggressive risks into strong results may reflect the overall frailness of new organizations, who often lack the skills and cushioning needed to ride out bad times (Hannan & Freeman, 1984). Taking aggressive yet reasonable risks may therefore be a skill that many young firms have yet to learn.

While young organizations bounced between cells 1 and 7, we found that older firms, those age 11 and up, bounced between cells 3 and 9 on the right side of Figure 1. In cell 3 were untroubled older firms -- those that had exceeded their aspirations or moderately underperformed them. As they aged, their future gains increased and their future losses decreased. As Figure 2 revealed, that tendency took over a decade to develop. Very young firms also recorded strong gains, but their early successes soon eroded because they lacked the path-dependent learning needed to protect their early positional advantages against imitators (cf. Barney, 1991). In time, however, some older firms developed such skills, and they enjoyed the combination of large gains and small losses in cell 3.

Finally, we found cell 9 to be inhabited by troubled older firms. When they experienced a large loss and took aggressive risks, their future performance became uncertain, as evidenced by their particularly large future gains and losses. In fact, if we look at the top lines graphed in Figures 2 and 3, we see that the variability of future performance generally increased with age among those that had fallen well short of their aspirations, which contradicts arguments in ecology and learning theory that time, repetition, and learning breed homogeneity (Hannan & Freeman, 1984; Levinthal & March, 1993). To us, this reflects the challenges that organizations face as they try to learn from experience in high-velocity settings where feedback is noisy and confusing, and superstitious learning is likely because booming demand causes some to mistake luck for skill.

Our results indicate that some older firms learned to cope with turbulence, uncertainty, and change, an instance of a dynamic capability (Teece et al., 1997). While they still stumbled occasionally, they recovered strongly, and more so as they grew older. In contrast, other older firms followed one large loss with another as their risk taking and change attempts failed to pay off. That trend worsened at higher ages, which suggests that their change management skills decreased with time because their routines increasingly stored superstitious knowledge about cause-effect relationships. Future studies might consider specific contributors to that process. For

example, what patterns of strong and weak performances are mostly likely to produce superstitious learning? Conversely, what patterns best promote the construction of dynamic capabilities? And if we consider decision processes within firms, how does the longevity of a top management team affect its capacity for adaptive and superstitious learning?

In summary, we draw three major conclusions from our findings. First, theories about positive and negative risk-return relationships should be seen as complementary rather than competing ideas. In this study, each was supported in some situations and contradicted in others. Thus, both theories are vital pieces of a larger and more comprehensive framework. Second, we conclude that evolutionary processes deserve a prominent place in that comprehensive framework because risk-return linkages change across time as firms and industries develop. Here, we found strong evidence that the time-paced learning associated with organizational aging influenced the relationship between risk and return. Other evolutionary forces are likely to affect that relationship as well, so future studies might examine learning by firms that repeatedly acquire and integrate other organizations (Karim & Mitchell, 2000), the lessons accumulated by firms that repeatedly change their organizational core (Amburgey et al., 1993), and processes that drive industry-level change, such as radical innovations (Tushman & Anderson, 1986). Rather than simply asking whether such developments increase or decrease average performance, we can assess their longitudinal effects on upside returns and downside risks and gain a richer understanding of both organizational evolution and the tradeoffs that managers face as they confront an unfolding sequence of future uncertainties.

Finally, we conclude that analyzing gains and losses in separate models offers major advantages. One is signaled by our finding that those outcomes followed distinct evolutionary trajectories as firms learned to avoid losses at much younger ages than they learned to sustain above-average gains. That occurred, we believe, because losses could be mitigated by adopting widely diffused professional business practices, while sustained advantage required idiosyncratic, firm-specific learning developed across long periods of time (cf. Barney, 1991; Dierickx & Cool, 1989). This suggests that future research should address not only theories of competitive advantage (e.g., the resource-based view), but theories of how firms learn to become average and avoid large losses, which may have distinctly different causes. While the strategy literature offers

numerous ideas about achieving advantage, it contains few if any about how to avoid disadvantage, which represents another opportunity for future study.

Like all research, this study has its limitations. As noted earlier, we lack profitability data, and while sales growth is a good indicator of performance in this setting, this limits direct comparisons between this study and others. Also, the personal computer industry is particularly dynamic and fast-paced, and while developments in information technology, including the Internet, are causing numerous industries to adopt a similar pace, other patterns may emerge in more stable environments.

Our goal in this study was sketch a middle-range theory of how risk-return relationships evolve in high-velocity environments. We hope that our findings and ideas will prompt others to undertake similar studies in other settings that are quite different in their pace and degree of technological intensiveness. In doing so, our understanding of risk, return, and evolutionary change is likely to be substantially enriched.

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**TABLE 1: Means, Standard Deviations, and Correlations of Key Variables**

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Gain magnitude	0.65	0.63																				
2. Loss magnitude	0.49	0.38	n.a.																			
3. Firm age	4.01	3.08	-0.17	-0.05																		
4. Perf. < aspirations	0.21	0.30	0.20	0.01	-0.18																	
5. Perf. > aspirations	0.36	0.56	-0.06	0.06	-0.10	-0.45																
6. Firm size	8.66	2.26	-0.18	0.04	0.52	-0.48	0.32															
7. Current products	4.39	7.01	-0.10	-0.10	0.48	-0.12	0.01	0.48														
8. New products	1.90	3.99	-0.03	-0.09	0.30	-0.05	0.05	0.36	0.91													
9. De alio entrant	0.21	0.40	0.01	0.06	0.32	-0.10	0.05	0.39	0.22	0.15												
10. Technology strategy	0.33	0.47	-0.02	0.14	0.22	-0.03	0.00	0.17	-0.01	-0.02	0.32											
11. Changed strategy	0.13	0.34	-0.01	0.03	0.39	-0.06	-0.00	0.18	0.14	0.10	0.12	0.34										
12. Change clock	0.47	1.51	-0.04	-0.02	0.48	-0.05	-0.03	0.23	0.31	0.25	0.16	0.32	0.79									
13. Population density	235.43	77.91	-0.08	-0.40	0.22	-0.07	-0.03	0.13	0.22	0.16	-0.13	-0.33	0.05	0.08								
14. Founding density	184.34	96.96	0.04	-0.32	-0.39	0.06	0.02	-0.18	0.01	0.06	-0.32	-0.49	-0.27	-0.25	0.70							
15. Total industry sales	16.28	7.79	-0.10	-0.39	0.29	-0.07	-0.04	0.18	0.32	0.25	-0.11	-0.32	0.02	0.10	0.91	0.71						
16. IBM Installed base	15.28	4.66	-0.05	-0.23	0.22	-0.05	-0.02	0.11	0.22	0.17	-0.13	-0.28	0.05	0.09	0.88	0.62	0.82					
17. Community size	14.85	2.32	-0.06	-0.31	0.14	-0.07	0.03	0.13	0.24	0.19	-0.16	-0.52	0.06	0.10	0.72	0.58	0.70	-0.15				
18. Community age	8.00	2.94	-0.04	-0.17	0.39	-0.05	-0.06	0.19	0.36	0.27	-0.14	-0.29	0.05	0.13	0.59	0.43	0.73	-0.15	0.55			
19. Community density	171.16	109.06	-0.04	-0.33	0.08	-0.06	-0.01	0.04	0.22	0.18	-0.22	-0.56	0.01	0.07	0.78	0.69	0.76	-0.21	0.80	0.44		
20. Failure $\lambda$	0.26	0.16	-0.00	-0.08	-0.07	0.06	-0.09	-0.31	-0.31	-0.31	-0.36	-0.22	-0.15	-0.06	0.30	0.29	0.26	0.25	0.13	0.35	0.24	
21. Gain probability	0.59	0.20	0.13	-0.28	-0.40	0.26	0.01	-0.22	-0.14	-0.08	0.00	-0.15	-0.07	-0.12	0.21	0.35	0.12	0.12	0.18	-0.22	0.21	-0.03

• N = 1,284 for statistics involving gains; N = 1,425 for statistics involving losses; N = 2,709 otherwise. Because gains are missing for loss observations and vice versa, gain and loss magnitudes do not have a correlation. In this table, gains and losses are recorded at time t, and all other variables at t-1.

**TABLE 2: GEE Models of Future Gain Magnitudes**

Variable	Model			
	(1)	(2)	(3)	(4)
Firm age <sub>i,t-1</sub>		-0.188 *** (0.055)	-0.273 *** (0.058)	-0.266 *** (0.053)
Firm age <sup>2</sup> <sub>i,t-1</sub>		0.006 ** (0.002)	0.010 *** (0.002)	0.010 *** (0.002)
Perf. < aspirations <sub>i,t-1</sub>		0.582 *** (0.144)	0.278 (0.178)	0.293 (0.169)
Perf. > aspirations <sub>i,t-1</sub>		0.080 (0.049)	0.053 (0.087)	0.075 (0.050)
Firm age x perf. < aspirations <sub>i,t-1</sub>			0.117 ** (0.039)	0.112 *** (0.033)
Firm age x perf. > aspirations <sub>i,t-1</sub>			0.007 (0.020)	
Firm size <sub>i,t-1</sub>	-0.080 *** (0.020)	-0.054 ** (0.021)	-0.061 ** (0.021)	-0.061 ** (0.020)
Current products <sub>i,t-1</sub>	-0.053 *** (0.013)	-0.050 *** (0.013)	-0.049 *** (0.012)	-0.048 *** (0.013)
New products <sub>i,t-1</sub>	0.079 *** (0.023)	0.069 ** (0.024)	0.072 ** (0.024)	0.072 ** (0.024)
De alio entrant <sub>i</sub>	0.193 * (0.089)	0.364 *** (0.094)	0.381 *** (0.094)	0.383 *** (0.094)
Technology strategy <sub>i,t-1</sub>	-0.041 (0.077)	-0.088 (0.076)	-0.073 (0.075)	-0.072 (0.075)
Changed strategy <sub>i,t-1</sub>	0.119 (0.128)	0.297 * (0.135)	0.337 ** (0.129)	0.336 ** (0.129)
Change clock <sub>i,t-1</sub>	0.006 (0.037)	-0.010 (0.037)	-0.023 (0.038)	-0.022 (0.037)
Population density <sub>t-1</sub>	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Founding density <sub>i</sub>	0.002 * (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Total industry sales <sub>t-1</sub>	-0.036 ** (0.011)	-0.009 (0.014)	-0.002 (0.014)	-0.003 (0.014)
IBM installed base <sub>t-1</sub>	0.021 (0.012)	0.016 (0.012)	0.014 (0.012)	0.014 (0.012)
Community age <sub>i,t-1</sub>	0.068 ** (0.022)	0.008 (0.026)	0.007 (0.024)	-0.006 (0.024)
Community density <sub>i,t-1</sub>	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Community sponsor <sub>i,t-1</sub>	-0.052 (0.219)	-0.057 (0.218)	0.119 (0.215)	0.134 (0.221)
Failure $\lambda_{i,t}$	-0.432 (0.263)	-0.577 * (0.244)	-0.586 * (0.251)	-0.582 * (0.246)
Gain probability <sub>i,t</sub>	0.202 (0.291)	-1.388 ** (0.478)	-1.658 *** (0.448)	-1.642 *** (0.449)
-2 * log likelihood	1276.4 ***	1258.5 ***	1248.9 ***	1249.1 ***

\*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ ; two-tailed tests.  $N = 1,284$ . Standard errors are shown in parentheses. Model 2 had better fit than model 1 ( $p < .01$ ); model 3 had better fit than model 2 ( $p < .01$ ). The fit of model 4 did not significantly differ from model 3 ( $p > .65$ ).

**TABLE 3: GEE Models of Future Loss Magnitudes**

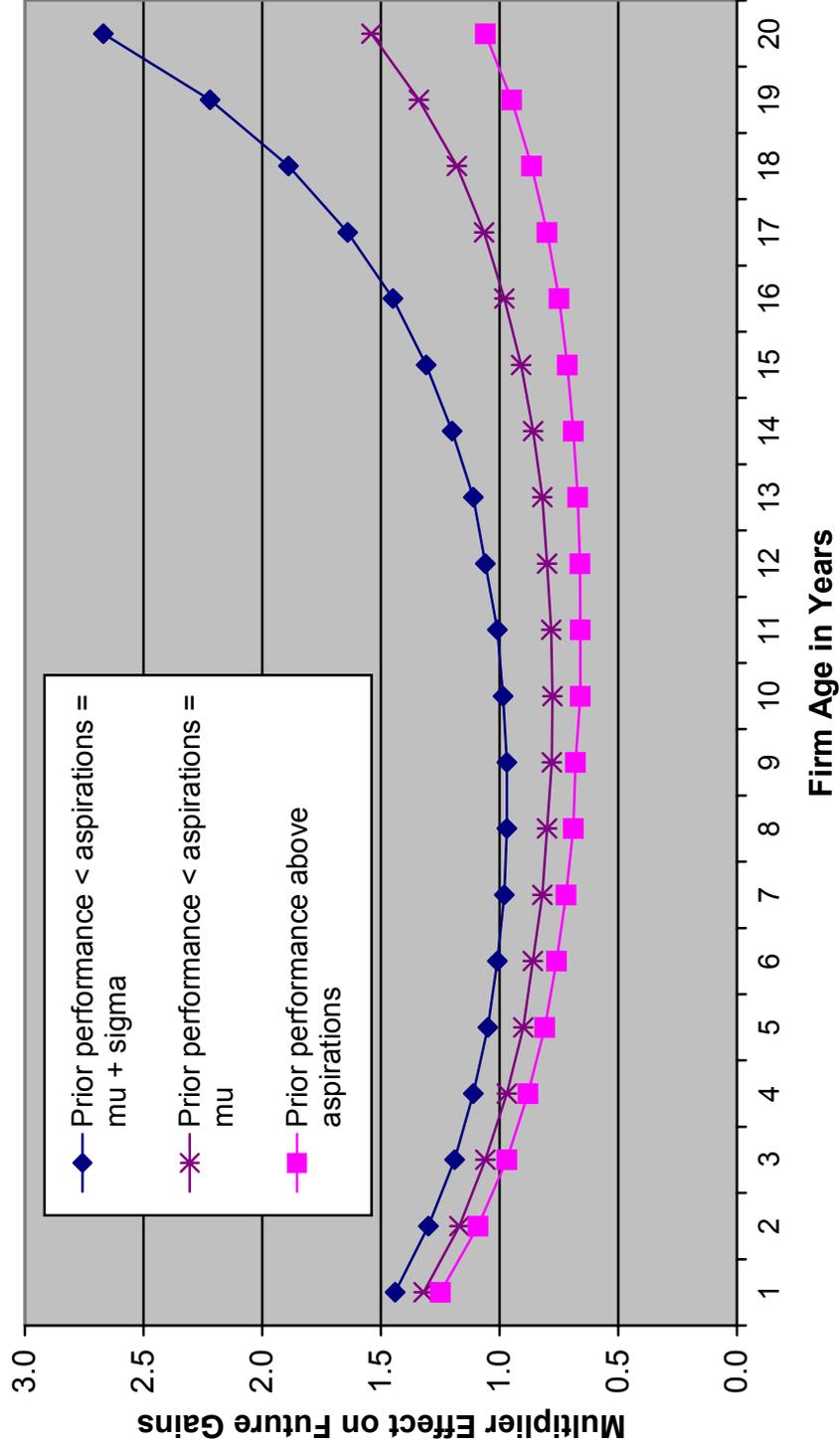
Variable	Model			
	(5)	(6)	(7)	(8)
Firm age <sub>i,t-1</sub>		-0.037 (0.022)	-0.069 ** (0.022)	-0.070 *** (0.021)
Perf. < aspirations <sub>i,t-1</sub>		0.296 ** (0.092)	-0.082 (0.126)	-0.088 (0.119)
Perf. > aspirations <sub>i,t-1</sub>		0.067 (0.040)	0.069 (0.064)	0.061 (0.039)
Firm age x perf. < aspirations <sub>i,t-1</sub>			0.097 *** (0.020)	0.099 *** (0.018)
Firm age x perf. > aspirations <sub>i,t-1</sub>			-0.002 (0.013)	
Firm size <sub>i,t-1</sub>	0.092 *** (0.013)	0.094 *** (0.014)	0.085 *** (0.014)	0.085 *** (0.014)
Current products <sub>i,t-1</sub>	0.004 (0.006)	0.008 (0.006)	0.009 (0.006)	0.009 (0.006)
New products <sub>i,t-1</sub>	-0.010 (0.011)	-0.014 (0.012)	-0.013 (0.011)	-0.013 (0.011)
De alio entrant <sub>i</sub>	-0.018 (0.073)	0.045 (0.078)	0.053 (0.075)	0.053 (0.075)
Technology strategy <sub>i,t-1</sub>	0.041 (0.053)	0.030 (0.053)	0.030 (0.052)	0.030 (0.052)
Changed strategy <sub>i,t-1</sub>	0.195 * (0.082)	0.240 ** (0.082)	0.239 ** (0.080)	0.238 ** (0.079)
Change clock <sub>i,t-1</sub>	-0.028 (0.024)	-0.033 (0.024)	-0.031 (0.023)	-0.030 (0.023)
Population density <sub>t-1</sub>	-0.025 *** (0.003)	-0.024 *** (0.003)	-0.024 *** (0.003)	-0.024 *** (0.003)
Population density <sup>2</sup> <sub>t-1</sub> /1000	0.048 *** (0.006)	0.047 *** (0.006)	0.047 *** (0.006)	0.047 *** (0.006)
Founding density <sub>i</sub>	0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Total industry sales <sub>t-1</sub>	-0.048 *** (0.008)	-0.035 ** (0.011)	-0.030 ** (0.011)	-0.030 ** (0.011)
IBM installed base <sub>t-1</sub>	0.141 *** (0.012)	0.136 *** (0.013)	0.138 *** (0.013)	0.138 *** (0.013)
Community age <sub>i,t-1</sub>	0.028 * (0.014)	0.008 (0.015)	0.001 (0.014)	0.001 (0.014)
Community density <sub>i,t-1</sub>	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Community sponsor <sub>i,t-1</sub>	-1.152 *** (0.193)	-1.043 *** (0.209)	-0.922 *** (0.216)	-0.918 *** (0.212)
Failure $\lambda_{i,t}$	0.282 (0.161)	0.242 (0.166)	0.237 (0.158)	0.237 (0.158)
Loss probability <sub>i,t</sub>	0.251 (0.186)	0.905 ** (0.327)	0.986 ** (0.300)	0.980 *** (0.295)
-2 * log likelihood	442.12 ***	432.12 ***	413.36 ***	413.46 ***

\*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ ; two-tailed tests.  $N = 1,425$ . Standard errors are shown in parentheses. Model 2 had better fit than model 1 ( $p < .05$ ); model 3 had better fit than model 2 ( $p < .001$ ). The fit of model 4 did not significantly differ from model 3 ( $p > .95$ ).

**FIGURE 1**  
**Potential Combinations of a Predictor's Effects on Future Gains and Losses**

		-	0	+
<b>Predictor's Effect on Future Losses</b>	-	<ul style="list-style-type: none"> <li>• Economic theory</li> <li>• Forces that decrease uncertainty</li> <li>• Positive risk-return relationships</li> </ul> <p align="right"><b>Cell 1</b></p>	<ul style="list-style-type: none"> <li>• Hygiene factors</li> </ul> <p align="right"><b>Cell 2</b></p>	<ul style="list-style-type: none"> <li>• Bowman paradox</li> <li>• Rare competencies</li> <li>• Negative risk-return relationships</li> </ul> <p align="right"><b>Cell 3</b></p>
	0	<p align="right"><b>Cell 4</b></p>	<p align="right"><b>Cell 5</b></p>	<p align="right"><b>Cell 6</b></p>
	+	<ul style="list-style-type: none"> <li>• Bowman paradox &amp; Prospect theory</li> <li>• Gambling by troubled firms</li> <li>• Negative risk-return relationships</li> </ul> <p align="right"><b>Cell 7</b></p>	<p align="right"><b>Cell 8</b></p>	<ul style="list-style-type: none"> <li>• Economic theory</li> <li>• Forces that increase uncertainty</li> <li>• Positive risk-return relationships</li> </ul> <p align="right"><b>Cell 9</b></p>

**FIGURE 2**  
**Predicted Influence of Firm Age on Future Gains**  
**at Three Levels of Prior Performance Relative to Aspirations**



**FIGURE 3**  
**Predicted Influence of Firm Age on Future Losses**  
**at Three Levels of Prior Performance Relative to Aspirations**

