Decomposing Uncertainty and Its Effects on Imitation in Firm Exit Decisions

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This study examines the effects of different uncertainty types on interorganizational imitation in firm exit decisions. We draw on herding models to conceptualize exit decisions as being based on a firm's private information, which the firm updates with information inferred from observing the actions of others. We posit that different types of uncertainty differentially affect this observational learning process; in particular, we propose that certain uncertainty types attenuate (rather than foster) observational learning and subsequent imitation. We test this theory using a 29-year panel data set on the exit of private venture capital firms. Our results indicate that observational learning does influence imitation in firm exit decisions, and they also suggest that a common belief—that uncertainty enhances imitation—does not apply to all types of uncertainty. Specifically, we find that uncertainty fosters imitation only when it is idiosyncratic to the firm; uncertainties that are common to all firms, in contrast, actually reduce reliance on observational learning. By decomposing uncertainty into different types and explicating their effects on imitation, we demonstrate that this relationship is more nuanced than previously assumed and, in addition, highlight the role of deliberate information processing in imitation.

Key words: imitation; uncertainty; organizational learning; herding; firm exit

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Introduction

What is the role of uncertainty in shaping interorganizational imitation? A central thesis in the seminal work of Cyert and March (1963) is that imitation figures prominently in the response of firms to uncertainty. Not only does imitation allow a firm to economize on search costs (Cyert and March 1963), it also ensures that adopted behaviors are legitimate (DiMaggio and Powell 1983). A large body of literature has thus assumed that uncertainty drives imitation (e.g., Greve 1995, Haunschild and Miner 1997, Henisz and Delios 2001, Rao et al. 2001). In his review of how imitation is viewed from different theoretical perspectives, Greve (1996) remarks that, in spite of their varied assumptions, these perspectives are in agreement that uncertainty leads to imitation.

Because this proposition is oftentimes seen as self-evident (see Strang and Still 2006), few studies have sought to examine explicitly the relationship between uncertainty and imitation. Toward this end, two questions are relevant: Is uncertainty *necessary* for imitation, and how does uncertainty *moderate* imitation? Previous research on these questions hints that uncertainty and imitation interrelate in ways that are more complicated than is commonly assumed. For instance, Haunschild (1994) and Greve (2009) find that imitation may occur in the absence of uncertainty. Yet Haunschild (1994) acknowledges that examination of uncertainty as a nec-

essary condition is difficult because few (if any) decision scenarios are completely devoid of uncertainty.

As for the moderating effect, Strang and Still (2006) find that an increase in uncertainty resulting from causal ambiguity can actually suppress, rather than foster, imitation. The reason is that causal ambiguity makes it difficult for firms to identify what, exactly, to imitate. Other researchers have examined specific aspects of this moderating role: Haunschild (1994) investigates whether uncertainty differentially affects the selection of imitation targets, and Haunschild and Miner (1997) explore how uncertainty moderates the selection of imitation modes. Our study is situated within this latter line of inquiry, but rather than asking how uncertainty moderates the selection of imitation targets or modes, we examine how different *types* of uncertainty moderate a firm's tendency to imitate. This is an important question because it allows for the possibility of isolating the causal mechanism driving imitation and of understanding the role of deliberate information processing in imitation.

Uncertainty reflects the lack of information or knowledge, which translates into difficulties in accurately assessing current and future decision situations (Beckman et al. 2004, Henisz and Delios 2004, Milliken 1987). Scholars have developed typologies of uncertainty based on the different sources from which it arises (Beckman et al. 2004, Leblebici and Salancik 1981,

Milliken 1987). Although research has shown these different types to have distinct effects on a variety of firm behaviors, including network partner selection (Beckman et al. 2004) and governance choices (Carson et al. 2006), we yet have only a limited understanding of their differential effects on imitation. This is due in part to a dearth of studies distinguishing between uncertainty types while exploring their effects on imitation. Moreover, the few studies that explicitly address this relationship have yielded inconclusive results (Henisz and Delios 2001, 2004). Our paper seeks to address this gap by identifying uncertainty types that are salient in the context of firm exit decisions and by examining how these different types moderate imitation.

Organization theorists often use the term imitation in a generic sense to “indicate that an organization is positively influenced by what others do” (Strang and Still 2006, p. 102). Different theoretical perspectives have proposed a variety of processes to underlie this broad notion of imitation, including mimetic isomorphism (DiMaggio and Powell 1983), observational learning (Banerjee 1992, Bikhchandani et al. 1992), and resource availability (Hannan and Carroll 1992). Here, we conceptualize it as resulting from observational learning, the central mechanism that drives interorganizational dependency in herding models (Banerjee 1992, Bikhchandani et al. 1992). This literature defines observational learning as “the influence resulting from rational processing of information gained by observing others” (Bikhchandani et al. 1998, p. 153). The key idea is that “actions reflect information” (Bikhchandani et al. 1998, p. 154); thus, when organizations face a decision problem, they update their private information about the problem by using information inferred from the observed actions of others. The resulting similarity in firms’ behaviors is known as “herding” or imitation (Hirshleifer and Teoh 2003).

To examine how different types of uncertainty moderate observational learning and imitation as regards firm exit, we begin by conceptualizing exit decisions to be forward looking; that is, they depend not only on current performance data but also on the firm’s expected future performance, which in turn is related to expected future market conditions (Dixit and Pindyck 1994, Murto and Välimäki 2011). These expectations are important because positive future performance or market outlooks can make exit unwarranted even when the firm’s current performance is weak; conversely, if outlooks are poor, then exit may be sensible even when the firm is performing well.

Thus, part of the uncertainty surrounding exit decisions stems from the volatility in both firm performance and market conditions. Volatility refers to the rate and randomness of change, and it creates uncertainty about the future, “for by definition, it is unpredictable change” (Leblebici and Salancik 1981, p. 579). However, the uncertainties stemming from volatile firm performance

and volatile markets differ in type. Uncertainty that results from volatile firm performance is idiosyncratic and therefore uniquely affects that firm’s decision making; we refer to this type as *firm uncertainty*. In contrast, uncertainty that results from market volatility is common to all firms and therefore affects their decision making to the same degree (Beckman et al. 2004); this type is *market uncertainty*. Finally, a third type of uncertainty stems not from volatility but rather from others’ actions revealing inconsistent information, which inhibits the focal firm from updating its private information; we refer to this as *inference uncertainty*.

We hypothesize that firm uncertainty fosters reliance on observational learning, whereas market uncertainty and inference uncertainty attenuate such reliance. This follows because volatility in a firm’s performance complicates its own predictions of future performance and thus introduces uncertainty into its exit decision; in such cases, the firm relies more heavily on information inferred from the actions of others. In contrast, volatility in market conditions introduces uncertainty into every firm’s decision making and so renders each firm’s actions similarly “uninformed.” This dynamic reduces the precision attributed by a firm to the information it infers from other firms’ actions and thereby reduces observational learning. Such learning is also reduced by inference uncertainty, as inconsistencies in others’ actions prevent the firm from updating its private information into any one single direction.

We test our theory using longitudinal data on the exit decisions of 1,342 private venture capital (VC) firms from 1980 through 2008. The results are consistent with exit decisions being shaped by imitation via observational learning and also support our hypotheses that different uncertainty types have distinct effects on imitation. As such, our results provide a necessary link in the causal chain connecting abstract imitation processes to concrete organizational actions, and, in particular, call attention to the role that deliberate information can play in these processes. Our study also contributes to the literature on firm exits. In describing firm exit as a decision problem subject to informational influences from others, we offer a more inclusive conceptualization of the factors shaping firm exits.

Literature Review

We view firms as basing their exit decisions on private information that is updated by inferences from the exit/entry decisions of other firms. This paper is thus associated with prior studies relating the exit decision of a focal firm to exits and entries of other firms. Two streams of research are relevant. The first invokes, as we do, a form of observational learning to shape exit decisions. However, the extant literature focuses on segment or product market exits whereas we focus on exit of the

firm itself (i.e., firm disbandment). The second stream of relevant research explores, as we do, the relations between firm exit and prior exits (and entries). However, studies in this stream invoke causal processes that differ from the observational learning mechanism proposed here. We discuss each set of studies in turn.

Exit from Product and Market Segments

Organization theorists have examined how exit from product markets, market segments, or foreign markets is shaped by other firms exiting previously (Belderbos et al. 2011, Dobrev 2007, Greve 1995, Henisz and Delios 2004). Various causal mechanisms have been invoked to explain this interorganizational dependency. Greve (1995) theorizes that insufficient information about the right course of action causes firms to examine the actions of their competitors. The focal firm's evaluation of market segment exit is influenced by other firms exiting because it suggests that they view exit as an appropriate action. Henisz and Delios (2004) reference various perspectives that relate prior exits to future exits from foreign markets: neo-institutional arguments, in which firms imitate the exit decisions of others to secure legitimacy (DiMaggio and Powell 1983); "competitive bandwagon" arguments, whereby a firm follows others' exits because it fears that deviance carries performance penalties (Abrahamson and Rosenkopf 1993); and rational choice arguments (Banerjee 1992, Bikhchandani et al. 1992) similar to those advanced by Greve (1995). Dobrev (2007) highlights the role of cognitive identity, suggesting that a firm imitates others' exits "because consistency with the actions of those whose presence defines the firm's individual identity is its default mode for interpreting reality" (p. 1273). He additionally proposes that high numbers of exits, however, inhibit further exits because they weaken the collective identity as well as free up resources that make further exit unattractive.

Our conceptualization is grounded in the rational choice arguments employed by Greve (1995) and also invoked by Henisz and Delios (2004), but it is distinct nonetheless. First, analogous to herding models wherein firms learn both from others that adopt and from others that reject the behavior in question, we assume that firms infer information not only from others that exit but also from those that enter the market. Second, we focus on firm exit, not on the exit from product or market segments. This choice facilitates our study because it reduces the likelihood of imitation being driven by concerns of legitimacy or competitive disadvantage (given that such concerns are irrelevant once the firm exits). However, our focus on firm exit creates a challenge: for observational learning to be relevant to this type of exit, firm exit must not only result from (involuntary) firm failure; instead, it must be a decision problem that is subject to the informational influences of others. There is

evidence that the appropriateness of conceptualizing firm exit as a decision problem depends on the context (Bates 2005, Caves 1998). We elaborate on the suitability of our research context in the Research Setting section.

Firm Exit and Its Relationship to Prior Exits

Research in organizational ecology has paid considerable attention to the effects of both population density (e.g., Carroll and Hannan 1989a, b; Hannan and Freeman 1989) and population dynamics (Delacroix et al. 1989) on firm exit. For our study, arguments from population dynamics are of particular interest because this perspective focuses, as we do, on the dependence of a focal firm's exit on prior exits and entries (rather than density). In general, ecological theory conceptualizes firm exit as firm failure. Scholars invoking population dynamics most commonly predict (and often find) that prior exits free up resources that can be recycled by incumbents, reducing their risk of failure (Baum and Oliver 1992, Delacroix et al. 1989, Wade et al. 1998). Prior entries have also been related to subsequent exits, but not via a direct causal mechanism as proposed in our study. Instead, such analysis views prior entries as reflecting the emergence of a new niche; a negative relationship between prior entries and subsequent exits is thus interpreted as indirect evidence that incumbents are moving to that new niche, which in turn reduces their exit rates (Delacroix et al. 1989).

The differences between our study and the research on population dynamics in organizational ecology are pronounced. First, we interpret prior exits and entries to shape subsequent exits via informational effects, rather than resource effects as commonly posited by organizational ecology (and, as mentioned, thus also view firm exit as a decision problem). Second, expected relationships are mostly of opposite signs. The observational learning mechanism proposed here implies a positive relationship between prior exits and future exits, whereas the resource release mechanism proposed by population dynamics implies a negative relationship.¹

Research Setting

Viewing firm exit as shaped by observational learning requires a research context in which exit can be fairly described as a decision problem. In addition, exploring how different types of uncertainty moderate the exit process requires a research context in which exit decisions are made under considerable uncertainty. One setting that meets these conditions is the private VC industry. Venture capitalists are professional investors who raise funds from wealthy individuals, insurance companies, pension funds, and other institutional investors that wish to take equity positions in entrepreneurial ventures. The dominant organizational form in the private VC industry is limited partnership: fund managers (the general

partners) and fund providers (the limited partners) create a partnership as a vehicle to invest in, grow, and eventually sell off entrepreneurial ventures (Kenney and Florida 2000).

Firm Exit in the Venture Capital Industry

The common but one-dimensional view is that firm exit reflects poor firm performance. A more comprehensive perspective suggests that, although firm performance matters, it is the comparison of firm performance with opportunity costs and noneconomic factors that is key (Bates 2005, Caves 1998). This is especially true for small, human capital-intensive firms whose exits are not burdened by fixed costs or pension policies (Bates 2005, Caves 1998). Bates (2005) shows that, for such firms, “the common practice of equating business closure with business failure is often unjustified” (p. 343). In fact, it is sometimes the more successful of these firms that exit once owners or executives can better deploy their talents elsewhere (Caves 1998). For firm exit in the accounting industry, Pennings et al. (1998, p. 439) similarly notes that “professionals with that very ability [to retain and attract clients] may dissolve an accounting firm when their reputation can secure them better [outside] employment opportunities.”

Venture capital firms match well the conditions for conceptualizing firm exit as a decision problem. They typically have but a few general partners, and as firms without many physical assets, they fit squarely into the category of small, “purely human capital [knowledge based] firms” (Zingales 2000, p. 1641). Field interviews that we performed for this study confirm this supposition. Interviewees mentioned that exits are often active decisions shaped by a confluence of factors that include firm performance, market outlooks, outside options, and lifestyle considerations. Likewise, Freeman (2005, p. 158) finds that some VC firms exit “simply because the general partners decide to pursue other interests and opportunities.”

It should be noted that an exiting VC firm does not usually disappear right away (Rider and Swaminathan 2011). This is because VC firms raise funds with fixed life spans (often 7–10 years) and must eventually return the proceeds from liquidated funds to their limited partners. So even though the general partners may “exit” in the sense of ceasing all new investments and fund-raising activities, they may still continue to manage the currently funded portfolio until the fund expires. In such cases, any funds raised but not yet invested are normally returned to investors. Examples include Bowman Capital, which returned more than \$1 billion to investors when it exited the VC industry in 2001 (Hakim 2001), and Octane Capital Management, which returned to investors what remained of the \$265 million it had raised (Cortese 2001). Alternatively, funds not yet expired at the time of exit can be sold on the secondary

private equity market as investment portfolios. This was the approach taken by AEA Technology in selling its portfolios to Collier Capital in 2005 (Collier Capital 2005) and to Vision Capital in 2006 (Vision Capital 2006).

Uncertainty in the VC Industry

Volatility is the hallmark of the venture capital industry. In its relatively brief history, this industry has seen repeated boom–bust cycles: periods of rapid growth in VC activity followed by periods of collapse. Because volatility reflects the future’s unpredictability (Leblebici and Salancik 1981), it is a key source of uncertainty affecting decisions in the VC industry. Volatility and resultant uncertainty manifest at both the industry and the firm levels.

At the industry level, much of the volatility in venture capital activity is driven by volatility in market fundamentals. The overall health of the VC industry depends fundamentally on a vibrant public equity market (Black and Gilson 1998, Gompers and Lerner 2001). For example, consider that the growth of VC activity in the early 1980s, its decline in the late 1980s, and its subsequent unprecedented growth again in the 1990s were matched by a corresponding rise, fall, and rise in initial public offering (IPO) market activity. Venture capitalists are sensitive to this link; Gompers et al. (2008) analyze more than 30,000 VC investment decisions between 1975 and 1998 and find that they are highly responsive to market signals of investment opportunities. High expected returns through the stock market can attract greater VC investment and new entrants into the industry. Conversely, depressed public equity markets result in the scaling back of investments and in firms withdrawing from the industry. Given this interrelation between equity markets and venture capital activity, volatile stock markets directly translate into volatility in VC activities and thus generate uncertainty about future outlooks. Public equity markets can further compound this uncertainty by overvaluing particular sectors or companies (e.g., Internet retailers and communications companies in the early 2000). Overall, this uncertainty commonly leads to widely different assessments of the VC industry’s future. For example, in the autumn of 2006, longtime venture capital firm Sevin Rosen viewed the industry as broken (Carlsen 2008) while other VC firms saw it as promising (Moore 2006).

At the firm level, volatility in VC firm performance results in part from volatile markets (Cochrane 2005, Kaplan and Schoar 2005). Even so, some of this performance volatility remains idiosyncratic to the firm in that the success (and its unpredictability) of each firm is affected by unique factors. Venture capital firms specialize in high-risk investments in developing entrepreneurial ventures with unproven technologies. It is typical for only a few investments in the VC portfolio to account for a large portion of its returns, and many

result in a net loss (Sahlman 1990). Accurately evaluating ventures' prospects is thus key to a VC firm's performance, as is timing the market to maximize the returns from taking each venture public (Gompers and Lerner 2004). Accurate evaluations and optimal IPO timing rely heavily on the general partners' skills (Doerflinger and Rivkin 1987, Sørensen 2007), an intangible asset that is difficult to observe directly and that cannot be automated to ensure consistent performance.

Overall, this uncertainty—at both the industry and the firm levels—makes for an attractive setting in which to examine how different uncertainty types moderate imitation. Indeed, previous research has documented that imitation is an important behavioral heuristic in VC investment choices and practices (Gaba and Meyer 2008, Gompers and Lerner 2001). Anecdotal evidence from our interviews also suggests that imitation plays a role in decision making, including firm exit decisions. For example, one interviewee mentioned that “this is a very insecure, incestuous, and promiscuous business. So there is always a sense of ‘did I miss something?’” Another remarked that “with these years of downturn, you start wondering what to do, and you look to others to see how they are responding: Are they downsizing, are they leaving?”

Development of Hypotheses

Observational Learning and Firm Exit

In the basic structure of herding models, a decision maker “starts with some private information, obtains some information from predecessors, and then decides on a particular action” (Bikhchandani et al. 1998, p. 153). Bounded rationality causes each decision maker's private information to be imprecise or incomplete. She thus attends to the information revealed by predecessors since she expects, rightly or wrongly, that as the information accumulates, it becomes more precise so that its consideration improves decision results (Bikhchandani et al. 1998, Hirshleifer and Teoh 2003).² This inference effort is quite deliberate; that is, the decision makers as conceptualized here align closely with the Rao et al. (2001) notion of cognitive “misers” (who use heuristics to reduce search costs while increasing decision accuracy) as distinguished from the notion of cognitive “dopes” (who blindly imitate others).

In line with this reasoning, we assume that each firm starts by forming an expectation about overall market conditions and its own future performance (which, via (implicit) comparisons involving opportunity costs and outside options, determines the attractiveness of exit). Each firm then updates this private information with information inferred from the actions of other VC firms. The firm expects that as others' information pools, it more precisely reflects the value of firm exit, thereby

allowing for better decision results. In this way, subsequent exit decisions are informed by a combination of private information and information inferred from others' actions.

Herding models posit that decision makers infer information from others who adopt or reject the action in question, with adopters revealing their belief that the action is desirable and rejecters revealing the opposite. Translating this structure into our context suggests that VC firms update their private information about exit (the action under study) with information inferred from exiting firms (adopters of the action) and from nonexiting firms (rejecters of the action). Exiting firms reveal that their private information warrants exit. Although some of these firms may be failing, others could survive yet exit nonetheless (because, e.g., their general partners find outside options more attractive under the circumstances). In either case, the message from exits is clear: remaining in the market is undesirable. As the focal firm incorporates this message into its own exit decision, its propensity to exit increases as well.

In contrast, nonexiting firms send the opposite message. However, a strict translation of the herding model—so that VC firms infer information from such nonexits—entails an implausible scenario. The reason is that the cognitive task of attending to these firms would be too great: unlike firm exits, each nonexit is a “non-event” that can easily go unnoticed (Denrell 2003). Additional challenges would include delineating the relevant risk sets of nonexits as well as distinguishing firms that reject exit because they view it as unwarranted from those that simply have not yet contemplated it (Terlaak and Gong 2008). Given these considerations, we theorize that firms infer information not from nonexits but rather from the *entry* of others into the VC market. Each entry is an event that is more easily discerned as firms scan their environments when analyzing competitors (Porac et al. 1995). Furthermore, entries are both fewer and clearly delineated. Yet most important for the development of our theory is that the message conveyed by entrants is similar, if not identical, to that conveyed by nonexits: both indicate that expectations of future firm performance and market conditions are positive, which makes it desirable to participate in the market. After all, general partners found a VC firm only if they see these outlooks as promising.

Our claim that entering firms signal positive information is in line with the one in organizational ecology that initial entries into a market are a sign to others of opportunity and a generally positive climate (Delacroix and Carroll 1983). However, whereas studies in ecology focus on entrants factoring this information into their entry decision so that “an emulation process by which births trigger births” ensues (Delacroix and Carroll 1983, p. 279), we argue here that incumbents factor it into their exit decision so that they become less inclined to exit.

HYPOTHESIS 1A (H1A). *Observation of prior firm exits from the VC industry increases the exit probability of the focal VC firm.*

HYPOTHESIS 1B (H1B). *Observation of prior firm entries into the VC industry decreases the exit probability of the focal VC firm.*

Observational Learning and Uncertainty Types

Whereas a lack of precision in each firm's private information (a consequence of bounded rationality) is the initial trigger for a firm to infer others' information, elevated levels of uncertainty types may further moderate this inferential exercise. Avery and Zemsky (1998), for instance, develop a theoretical model to examine how different uncertainty types in financial markets differentially affect herding and contrarian behaviors among traders. In an empirical study, Hwang and Salmon (2004) find evidence that when markets are in crisis and thus highly uncertain, traders herd less. In a related vein, we investigate how observational learning in firm exit is moderated by three uncertainty types as defined earlier: firm uncertainty, market uncertainty, and inference uncertainty.

Firm Uncertainty. Volatility in firm performance is an issue with which VC firms routinely contend (Cochrane 2005, Kaplan and Schoar 2005). As outlined previously, market conditions in the VC industry are highly volatile, and part of this volatility translates into volatility in firm performance. Yet even when holding constant the effect of market volatility, there remain a number of firm-specific factors capable of inducing volatility in a VC firm's performance, thereby increasing the idiosyncratic uncertainty for each firm. These factors include the riskiness of the entrepreneurial ventures in which the firm has invested and the firm's heavy reliance on human capital skills.

For decision makers, volatile data introduce uncertainties to their decision making because greater volatility and variance is associated with higher degrees of randomness (March 1994). In particular, volatile data hamper inferences because greater variance in observations interferes with estimations of their distribution, which makes it difficult for decision makers to interpret those observations (Hogarth 1987, Rhee et al. 2006). Herding models have considered the consequences of data that is difficult to interpret. Hirshleifer and Teoh (2003) suggest that decision makers become more susceptible to informational influences from others as the difficulty of interpreting their own data increases. This is because decision makers seek to make accurate decisions; to the extent that difficult-to-interpret data increase the imprecision of their private information, the value of inferring others' information (that, in sum, is presumably more precise) increases. Along these lines, studies show that auditors and analysts rely

more heavily on observational learning the more difficult it is to disentangle their firm's accounting (DeBondt and Forbes 1999, Kim and Pantzalis 2003). Social psychologists also advance arguments in support of this notion. Using the concept of informational conformity, which is defined as "conformity to others' positions when the concern is to make accurate and valid judgments" (Cialdini and Trost 1998, p. 162), they find that greater task difficulty increases reliance on others' positions for making judgments (Coleman et al. 1958).

The notion that volatility in a VC firm's performance leads to data that complicate predictions about future performance and thus introduces idiosyncratic uncertainty into the firm's exit calculus—combined with the idea that such data increase reliance on observational learning—leads us to propose that such volatility strengthens that firm's reliance on observational learning in its exit decision.

HYPOTHESIS 2A (H2A). *Uncertainty resulting from a firm's performance volatility will strengthen the positive relationship between observed prior exits from the VC industry and the exit probability of the focal VC firm.*

HYPOTHESIS 2B (H2B). *Uncertainty resulting from a firm's performance volatility will strengthen the negative relationship between observed prior entries into the VC industry and the exit probability of the focal VC firm.*

Market Uncertainty. Unlike uncertainty that stems from volatile firm performance and thus is idiosyncratic to the firm, uncertainty that stems from volatile markets is common to all VC firms. By complicating their predictions of future market developments, this type renders equally uncertain the exit (and entry) decisions of every VC firm. One consequence is that the actions of others may become less informative. Recognizing this dynamic serves to qualify the assumption from observational learning that because action reflects information, considering those actions can usefully inform decision making.

Research suggests that decision makers consider the precision of the information that others' actions reveal. Organization theorists find that firms pay special attention to others whom they believe to be well informed (Baum et al. 2000, Greve 1998). Herding models similarly suggest that decision makers attend more closely to the information revealed by "fashion leaders," i.e., decision makers that are expected to have particularly precise information (Bikhchandani et al. 1998). We argue that if the selection of targets to imitate is shaped by the perceived precision of revealed information, then (by extension) so should the likelihood of relying on observational learning in the first place. Specifically, if decision makers expect that some event makes others' information more imprecise, then the value of inferring this information diminishes because it may no longer improve

decision accuracy. As a result, they rely less on observational learning. Henisz and Delios (2004) pick up on this idea when they argue that in the context of exits from foreign markets, observed exits allow managers to infer others' calculations on the expected level of profitability and that "based on their assessment of the accuracy of the information signal in these observations, managers may update their own prior beliefs regarding profitability levels" (p. 393, emphasis added).

Of course, market volatility not only increases the uncertainty (and thus imprecision) in the information inferred from others but in the private information of the focal VC firm, too. As a result, less reliance on others' information does not imply that the focal firm has gained relative confidence in its own information. Instead, given that it is equally uncertain, it may seek information from other trusted outside sources. In line with this, Strang and Still (2006) show that as the causal ambiguity surrounding projects in the banking industry increases, decision makers attend less to the information revealed by other banks and more to the information provided by consultants and academics. Applying this line of thought to our context then suggests that, because market volatility limits the precision of inferred information by increasing the uncertainty in each firm's decision to exit (or enter), decision makers will discount such information and thus reduce their reliance on observational learning.

HYPOTHESIS 3A (H3A). *Uncertainty resulting from market volatility will weaken the positive relationship between observed prior exits from the VC industry and the exit probability of the focal VC firm.*

HYPOTHESIS 3B (H3B). *Uncertainty resulting from market volatility will weaken the negative relationship between observed prior entries into the VC industry and the exit probability of the focal VC firm.*

Inference Uncertainty. Our final type of uncertainty does not arise from the difficulty of predicting the future; instead, it arises from difficulties that firms encounter when interpreting the information inferred from other firms' actions. In particular, with exits (entries) indicating that exit is (not) warranted, just what is a VC firm to infer from simultaneous observations of exits and entries?

Herding models have grappled with the consequences of inferred information inconsistencies for imitation. The stylized decision rule proposed by Bikhchandani et al. (1998) dictates that when the number of predecessors who adopt the behavior under study equals the number of those who reject it, decision makers should disregard all information inferred from others. The spirit of this rule is that reliance on observational learning should be reduced when inferred information is inconclusive. Smith and Sørensen (2000, p. 372) likewise suggest

that inferential learning declines when "history offers no decisive lesson for anyone," so that decision makers are left unsure about what to infer from the mix of preceding actions. Cameron (2005) captures this notion empirically in a study on updating beliefs in the context of assessing the risks of climate change. Cameron shows that decision makers who face conflicting external information reduce the attention paid to such data when updating their private information. Similarly, studies in social psychology on informational conformity find that unanimity in the information revealed by others is important, with a lack of such unanimity reducing the decision maker's reliance on others' information (Asch 1955, Morris and Miller 1975).

Rhee et al. (2006), in a study of automobile firms imitating each other's niche-width changes, develop a related argument. Specifically, they propose that when the variance in observed niche-width changes is large, firms imitate less: "Decision makers confronting conflicting mimetic requirements and practices find it difficult to make an imitation decision because conformity to one undermines the isomorphic support of other elements" (p. 504). Even though we draw on rational choice theory, whereas Rhee et al. use institutional theory, the two studies' arguments are roughly parallel. In essence, both posit that obstacles to processing observed information—caused by inconsistent information (as we suggest) or by heterogeneous information (as explored in Rhee et al. 2006)—reduce imitation.

HYPOTHESIS 4A (H4A). *Uncertainty resulting from inconsistency in inferred information will weaken the positive relationship between observed prior exits from the VC industry and the exit probability of the focal VC firm.*

HYPOTHESIS 4B (H4B). *Uncertainty resulting from inconsistency in inferred information will weaken the negative relationship between observed prior entries into the VC industry and the exit probability of the focal VC firm.*

Empirical Analysis

Sample and Data

We relied on the VentureXpert database, provided by Securities Data Company, as the primary data source for testing the hypotheses. Our sample comprised all U.S. private VC firms included in the VentureXpert database from 1980 through 2008. We began with year 1980 because it is viewed by most as the onset of the modern VC industry (Gompers and Lerner 2004, Kenney and Florida 2000). We focused on private VC firms and thus excluded other private equity sources of financing, many of which have objectives and procedures that differ sharply from those of private VC firms. Hence conflating these various financing types would likely have

confounded our results. Over the 29-year time period of the study, we tracked 1,342 VC firms; of these, 333 exited the market, a rate slightly lower than 25%.

Measures

Dependent Variable. We coded a dummy variable that takes on the value of 1 if the focal VC firm exits at time t (the exit year) and 0 prior to that date. To code this variable, we need two pieces of information: (i) the investment status of each VC firm as either active or inactive (or defunct) and (ii) the year in which the firm's status changed from active to inactive (or defunct). The VentureXpert database provides the following five-fold classification of the investment status of each VC firm: "defunct;" "inactive;" "actively seeking new investments;" "making few, if any, new investments;" and "reducing investment activity." Although the database records the current investment status of each VC firm, it does not give the year in which the status changed (say, from active to inactive). So we first we coded as *exits* all firms classified as defunct or inactive at the end of our observation window and coded as *active* all firms classified as actively seeking new investments. Second, for the firms classified as exits, we used their year of last investment (as reported by VentureXpert) to identify the year of exit; that is, we coded the exit year as the year following the year of last investment. Of the firms in our sample, 36 were categorized as either making few, if any, new investments or reducing investment activity. Because these VC firms were winding down their investment activity, we classified them as exits if their last investment occurred during or before the year 2001. This criterion resulted in three additional exits, but our results are robust to the exclusion of these three firms altogether.

We performed a series of checks to ensure the accuracy of our coding for both the status (exit versus active) and the exit date. To check the status coding, we first confirmed that each firm classified as an exit had made no new investments between its coded exit date and 2008; for firms classified as active, we confirmed that they were, in fact, making new investments. Second, we examined the fund-raising patterns of these VC firms. For this we used VentureXpert to confirm that no VC firm coded as an exit raised any new funds after its coded exit date. Third, we drew a random sample of firms from our sample and then used LexisNexis searches of business press articles, venture capital newsletters, and firm websites to confirm the status assigned via our coding rules.

We also evaluated the validity of coding the exit date as the first year of continuous noninvestment by a VC firm. First, summary statistics show that 92% of VC firms invest in consecutive years. Second, we used our data to test for whether a one-year investment gap predicts no further investments in subsequent years; we find

a strong and significant relationship ($z = 12.27$, $p = 0.000$), confirming that a one-year investment gap is a good indicator of exit. Third, for a randomly drawn sample of firms coded as exits, we used *Pratt's Guide to Private Equity and Venture Capital Sources* to confirm that the exit year as coded in our data matches the first year for which the firm was no longer listed in the directory. Finally, VC partners themselves confirmed in interviews that they view an entire year of noninvestment as a signal of current or impending exit.

Independent Variables. To test Hypotheses 1A and 1B, we created the variables *Prior exits* and *Prior entries*. *Prior exits* represents the number of VC firms that exited at time $t - 1$, were located in the same geographical state as the focal VC firm, and had the same investment focus as given by VentureXpert (which classifies such focus as early-stage, late-stage, or balanced). Similarly, *Prior entries* is a count of all VC firms that entered the VC market at time $t - 1$ and shared the geographical state and investment focus of the focal firm.³ We required prior exits and entries to be located in the same state as the focal firm and to share its investment focus because these attributes make it likely that the firm actually attends to these exits and entries (Baum et al. 2000, Greve 1998)—a critical requirement for observational learning. We follow the lag structure in prior imitation studies (Rao et al. 2001, Rhee et al. 2006) and count prior exits and entries in one-year windows. This time window is plausible in our context because the outlooks for performance and markets change relatively quickly, which limits the value of information inferred from less recent exits and entries. However, it is possible that a firm's perception of others exiting lags more than a year behind their decisions to cease investment and fund-raising activities (our measure of exit). To account for this, we created alternative measures that capture exits and entries in two- and three-year windows (i.e., by summing exits and entries at $t - 1$, $t - 2$, and $t - 3$). Using these alternative specifications yielded very similar results. Because these are nonnested models, we use the Clarke (2003) distribution-free test to determine the model that fits best; this is the model with exits and entries at $t - 1$. Figure 1 graphs the total numbers of exits and entries by year summed across geographical states and investment focuses.

To test Hypothesis 2, we employ standard measures of firm performance volatility and define the variable *Firm volatility* as the last-five-year rolling standard deviation in firm performance (Miller and Leiblein 1996). We measure firm performance as described under the Control Variables section. *Firm volatility* and the independent variables defined hereafter are all lagged by one year.

To test Hypothesis 3, we exploit the interdependency between public equity markets and venture capital activity (Gompers and Lerner 2004) to measure *Market*

Figure 1 Number of Exits and Entries of VC Firms (1980–2008)

volatility by calculating the volatility in NASDAQ stock returns (Beckman et al. 2004). Following Campbell et al. (2001), we define stock market volatility as the annual standard deviation in the daily value-weighted excess return on the NASDAQ market portfolio. Excess return is calculated relative to the daily risk-free rate.

For Hypothesis 4, we draw on information theory to construct a measure of inference inconsistency. We need this measure to assess how inconsistent the information revealed by other firms entering and exiting the market is. Hunter and Konieczny (2004) argue that such a measure should reflect both the magnitude of inconsistency and the amount of available information. *Information inconsistency* is thus defined as the absolute difference between exits and entries divided by the sum of exits and entries:

$$\text{Information inconsistency} = -\frac{|\text{Exits}_{t-1} - \text{Entries}_{t-1}|}{\text{Exits}_{t-1} + \text{Entries}_{t-1}}.$$

The absolute difference in the numerator captures the magnitude of inconsistency, with larger differences indicating smaller inconsistencies. For example, a more consistent message is received from observing 20 exits and 2 entries (a difference of 18) than from 20 exits and 19 entries (a difference of 1). The sum of exits and entries in the denominator accounts for the amount of available information. Incorporating this sum scales the size of the contradiction, so that equal absolute differences (e.g., the difference between 100 exits and 99 entries and that between 5 exits and 4 entries) signify greater inconsistency as the total number of observations increases. Finally, for ease of interpretation, we multiply the term by -1 so that values of the variable increase as information inconsistency increases.

Control Variables. We use several control variables to isolate the effects of our theorized variables from other confounding influences. First, we control for density at the industry level. Density can influence firm exits by affecting both the industry's legitimacy and availability of resources (Carroll and Hannan 2000). Our *Density* measure counts the number of all private equity firms, not just private venture capital firms, competing in the U.S. VC industry in each year; we also include *Density*² to capture any nonlinear effects of density. Data for this variable come from the 2008 *National Venture Capital Association Yearbook*. In their development of location-based resource partitioning theory, Carroll (1985) and Swaminathan (2001) show that an increase in the level of industry concentration increases the exit rates of generalists competing to control the center of the resource space. To account for this effect, we include the annual *Four-firm concentration ratio*, defined as the investment share of the largest four VC firms in each state.

Venture capital firm performance is an important driver of exit decisions. It would be ideal if we could measure the performance of each fund managed by a VC firm over the fund's lifetime, but the returns on individual funds are not systematically available to outsiders because VC firms generally disclose their performance data only to the investors in the fund. Hence we adopt the usual approach and measure performance indirectly by examining the status of each venture in which the VC firm invested (Hochberg et al. 2007). Thus *Performance as IPO proportion* is defined as the annual cumulated number of the firm's ventures that ended in an IPO divided by the cumulated number of ventures in its portfolio (IPO dates are taken from the IPO database VentureXpert). We complement this "success" measure of performance with a "failure" measure: the variable

Performance as defunct proportion, which is similarly defined as the proportion of defunct ventures in the firm's portfolio.

Exit decisions may also be related to a firm's age and size in that older and larger VC firms likely access different types of resources to manage their operations (Carroll and Hannan 2000). We measure VC firm *Age* as the number of years since founding; to capture any nonlinear effects of age, we also include Age^2 . Firm *Size* is measured as the log of total dollar amount of investments made by a VC firm in entrepreneurial ventures each year. Finally, because early- and late-stage VC firms may differ in average performance and thus in their exit propensity, we also control for the firm's preferred investment stage focus (Guler 2007). We measure *Investment stage preference* using two dummy variables that indicate whether (or not) the focal VC firm listed the early or late stage as its preferred focus (balanced stage is the omitted category).

To capture the effects that public equity markets have on VC activities, the *Public equity market* variable measures the value-weighted annual return on the NASDAQ (including dividends). In a subset of our model specifications, we also include year dummies to account for other time-series variations common to all VC firms. Table 1 provides the summary statistics and cross correlations.

Model Estimation

We use a discrete-time event history methodology to model market exit. Our dependent variable $P_i(t)$, is the discrete-time hazard that VC firm i exits at time t , given that it is at risk of doing so:

$$P_i(t) = \Pr[T_i = t \mid T_i \geq t, \mathbf{X}_i(t)];$$

here, T is the discrete random variable giving the time of exit, and $\mathbf{X}_i$ denotes a vector of covariates that affect the exit decision. A discrete-time event model is an appropriate choice for our data because VC firms that enter the risk set after 1980, are lost as a result of missing data, or do not exit continue to contribute to the regression model exactly what is known about them (Allison 1982).

We use a complementary log–log specification because it does not impose symmetry in the error term and is recommended when the outcome of interest (here, VC exit) is relatively infrequent (Allison 1982). Organizational exit rates often show age dependence, but because the form of that dependence varies widely (Hannan et al. 1998a, b), we use a piecewise constant-rate model that allows the exit rate to change non-monotonically with age. All specifications include duration dummies to account for shifts in the baseline hazard rate. We also report robust standard errors clustered by firm.

Table 1 Summary Statistics and Cross Correlations ($N = 10,790$)

Variable	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Prior exits	0.92	1.47	1															
(2) Prior entries	3.50	5.45	0.46	1														
(3) Firm volatility	0.05	0.07	−0.02	0	1													
(4) Market volatility	1.47	0.78	0.21	0.26	0.03	1												
(5) Information inconsistency	−0.37	0.31	0.04	−0.50	0.02	−0.09	1											
(6) Four-firm concentration ratio	50.7	30.09	−0.51	−0.52	0.02	−0.11	0.37	1										
(7) Density (firms)	2.41	0.98	0.23	0.26	−0.02	0.61	−0.07	−0.19	1									
(8) Density ² (firms)	6.76	4.27	0.20	0.28	−0.03	0.64	−0.09	−0.17	0.98	1								
(9) Performance as IPO proportion	0.05	0.10	−0.02	0.01	0.33	−0.05	−0.01	−0.04	−0.1	−0.09	1							
(10) Performance as defunct proportion	0.06	0.10	0.07	−0.04	−0.11	−0.02	0.07	−0.03	−0.02	0.01	−0.01	1						
(11) Age	8.82	7.66	0.06	0.03	−0.22	−0.05	0.02	−0.10	0.01	0.01	0.24	0.16	1					
(12) Age ²	136.5	255.1	0.07	0.06	−0.18	−0.01	−0.02	−0.10	0.03	0.03	0.20	0.11	0.92	1				
(13) Size ^a	8.77	3.30	0.05	0.06	−0.07	0.04	−0.03	−0.04	0.03	0.03	−0.01	−0.05	0.13	0.09	1			
(14) Investment preference (early stage)	0.61	0.49	0.22	0.30	−0.10	0.02	−0.21	−0.06	0.04	0.04	−0.13	−0.04	0	0.02	0.09	1		
(15) Investment preference (late stage)	0.25	0.43	−0.13	−0.21	0.06	−0.02	0.15	0.06	−0.05	−0.05	0.11	0.03	0.02	−0.01	−0.04	−0.72	1	
(16) Public equity market	−0.05	2.33	−0.16	0	−0.01	−0.31	−0.06	0.01	−0.07	−0.09	0	−0.02	0.01	0	0	0	0.01	1

Note. All time-varying variables (except Age, Age², Density, Density², and Four-firm concentration ratio) are lagged by one year.

^aNatural logs.

Results

Model 1 in Table 2 is the baseline model with controls. Greater firm performance volatility increases the likelihood of exit, as does market volatility. Inconsistency in inferred information has no direct effect on firms' exit propensities in Model 1, but it does exert a significant and negative effect in more fully specified models. The coefficients for *Density* and *Density*² indicate that, as density increases, exit propensities increase at a decreasing rate. This indicates that the VC market's infancy phase—and the attendant legitimacy effects of

density, which would tend to reduce exit—may have occurred prior to 1980 (Carroll and Hannan 1989b). The VC industry can actually be traced back to the 1940s (Kenney and Florida 2000), although it was not until 1980, which is the start of our observation period, that the industry gained sufficient legitimacy to witness momentum in inflowing funds, and hence players and competition. Note, though, that correlation among the density variables is very high such that multicollinearity, although not biasing estimates, prohibits us from identifying their effects as we add our independent variables in

Table 2 Effect of Prior Exits and Entries on Exit Probability (H1A and H1B)

Variable	Model 1	Model 2	Model 3
<i>Prior exits</i>		0.839*** (0.065)	0.860*** (0.077)
<i>Prior entries</i>		−0.172*** (0.039)	−0.178*** (0.039)
<i>Firm volatility</i>	1.526** (0.756)	1.646** (0.758)	1.709** (0.804)
<i>Market volatility</i>	0.505*** (0.126)	0.116 (0.145)	
<i>Information inconsistency</i>	−0.182 (0.228)	−2.186*** (0.280)	−2.195*** (0.299)
<i>Four-firm concentration ratio</i>	0.001 (0.003)	0.017*** (0.004)	0.017*** (0.004)
<i>Density</i> (firms)	1.380*** (0.462)	−0.147 (0.492)	
<i>Density</i> ² (firms)	−0.374*** (0.104)	0.003 (0.111)	
<i>Performance as IPO proportion</i>	−0.053 (0.757)	0.084 (0.806)	−0.038 (0.825)
<i>Performance as defunct proportion</i>	2.090*** (0.302)	1.686*** (0.348)	1.775*** (0.422)
<i>Age</i>	−0.103 (0.073)	−0.109 (0.068)	−0.072 (0.087)
<i>Age</i> ²	0.0002 (0.001)	0.0005 (0.001)	−0.0004 (0.002)
<i>Size</i>	−0.092*** (0.008)	−0.100*** (0.009)	−0.104*** (0.012)
<i>Investment preference</i> (early stage)	−0.371** (0.185)	−0.989*** (0.200)	−0.888*** (0.203)
<i>Investment preference</i> (late stage)	−0.404** (0.195)	−0.580*** (0.192)	−0.519*** (0.190)
<i>Public equity market</i>	−0.021 (0.029)	0.024 (0.028)	
<i>Constant</i>	−0.406 (1.589)	0.256 (1.527)	−0.239 (1.481)
No. of observations	10,790	10,790	10,790
No. of VC firms	1,342	1,342	1,342
Log-likelihood	−1,111.12	−998.90	−980.62
Joint significance test	284.47***	589.91***	30,482.32***
Year dummies	No	No	Yes
Marginal effect for <i>Prior exits</i>		0.035	0.036
Marginal effect for <i>Prior entries</i>		−0.012	−0.012

Notes. All models include duration dummies to account for time dependence in the baseline hazard rate. Robust standard errors (in parentheses) are clustered by firm.

Significant at 5%; *significant at 1%.

subsequent models.⁴ The coefficient for *Four-firm concentration ratio* does not matter in Model 1; in fully specified models, however, it is positive and significant. This suggests that VC firm exit rates increase with increases in industry concentration, as posited by resource partitioning theory (Carroll 1985).

As expected, firms with a higher proportion of defunct ventures in their portfolio are more likely to exit; our additional performance measure (proportion of ventures that went public) does not have a significant effect. We find no significant effect of firm age on probability of exit. However, firm size decreases the likelihood of firm exit. Investment preferences also matter in Model 1; we find lower exit probabilities among VC firms that focus on early- or late-stage ventures. Finally, the likelihood of exiting is negatively related to NASDAQ returns.

Effect of Exits and Entries. To test Hypotheses 1A and 1B, Model 2 adds *Prior exits* and *Prior entries* to the baseline specification of Model 1. The positive and significant coefficient on *Prior exits* supports H1A, indicating that the focal firm's exit probability increases as the number of exits by proximate and similar VC firms increases. The coefficient for *Prior entries* is negative and significant, which supports H1B, indicating that an increase in VC firms entering the market decreases the focal VC firm's exit propensity. A likelihood ratio test comparing Models 1 and 2 indicates a significant improvement in model fit. In terms of the magnitude of effects, the estimates from Model 2 imply that a 1% increase in *Prior exits* raises the probability of exit for a focal firm by 0.035 and that a 1% increase in *Prior entries* reduces the exit probability by 0.012. Furthermore, prior exits and entries affect subsequent exit even when we hold constant the uncertainties stemming from volatility in firm performance and markets, as well as from inconsistent information. Yet this result hardly entails that uncertainty is not a necessary condition for observational learning (Haunschild 1994). It more likely reflects that bounded rationality introduces elements of uncertainty (and hence imprecision) into each firm's private information and that these elements are not reflected in our uncertainty measures; indeed, they are perhaps so inherent in the decision that they cannot even be parceled out.

The VC industry goes through cycles of booms and busts. This implies that if capital flows and entrepreneurial opportunities in the VC industry dry up, we could observe a series of exits, and that this effect persists over time. In other words, an omitted variable—the flow of capital and/or entrepreneurial opportunities—may be driving entries and exits of VC firms in general and thus also the focal firm's exit decision. To ensure that our results reflect the hypothesized effects and are not a mere artifact of such omitted variables, in Model 3 we introduce year dummies that capture all temporal

variations affecting the industry as a whole. Including these dummies means that we can no longer identify variables that are purely time varying but identical across firms (e.g., *Density*, *Density*², *Market volatility*, and return on *Public equity market*). Even with this most demanding specification, we find that the coefficients for exits and entries are significant and have the predicted sign. Moreover, the marginal effect of exits and entries remain unchanged.

Interaction of Firm Uncertainty with Exits and Entries. Hypotheses 2A and 2B predict that volatility in firm performance increases the effects of *Prior exits* and *Prior entries*. Support for H2 requires that the cross-partial derivative of the exit probability with respect to *Firm volatility* and *Prior exits* be positive. However, the cross-partial derivative with respect to *Firm volatility* and *Prior entries* should be negative because the effect of entries on the focal firm's exit propensity is negative.

Model 4 in Table 3 includes the interaction of firm volatility with exits and entries, and Model 5 adds year dummies to Model 4.⁵ In both models, we obtain a positive coefficient for the interaction of exits with firm volatility and a negative coefficient for the interaction of entries with firm volatility. Neither of the interaction terms is statistically significant. Recall, however, that in nonlinear models, an interaction term's coefficient and standard error are not particularly informative. The reason is that in models with limited dependent variables, the effect of the interaction term (and of the standard error) depends not only on the interaction's coefficient but also on the coefficients for the two effects and on the values of all other variables (Ai and Norton 2003). As a result, neither sign nor significance of the interaction coefficients in Models 4 and 5 is indicative of the actual direction and significance of the interactions (Greene 2010, Hoetker 2007). Therefore, in Table 4 we follow best practices (Greene 2010) and present the attenuating effects of the interactions by calculating the marginal effects of *Prior exits* and *Prior entries* at various levels of *Firm volatility*.

Columns (1) and (2) in Table 4 show the marginal effect of *Prior exits* and *Prior entries*, respectively, at seven different levels of *Firm volatility*. Marginal effects and the corresponding standard errors are calculated (via the Delta method) using estimates from Model 4 in Table 3. As *Firm volatility* increases from three standard deviations below to three standard deviations above the mean, the marginal effect of *Prior exits* remains statistically significant and increases consistently.⁶ Similarly, the marginal effect of *Prior entries* increases in absolute terms (while remaining statistically significant) with an increase in firm performance volatility. Taken together, these results strongly support H2: uncertainty resulting from volatility in firm performance increases that firm's reliance on observational learning from prior exits and entries.

Table 3 Effect of Hypothesized Factors on Exit Probability (H2, H3, and H4)

	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
<i>Prior exits</i>	0.821*** (0.067)	0.845*** (0.080)	1.836*** (0.140)	1.862*** (0.167)	0.979*** (0.097)	0.990*** (0.109)
<i>Prior entries</i>	−0.157*** (0.041)	−0.164*** (0.040)	−0.368*** (0.065)	−0.367*** (0.071)	−0.374*** (0.064)	−0.369*** (0.066)
<i>Firm volatility</i>	1.833* (0.951)	1.954** (0.971)	1.382* (0.811)	1.394* (0.835)	1.676** (0.798)	1.733** (0.806)
<i>Market volatility</i>	0.122 (0.144)		0.510*** (0.146)		0.121 (0.139)	
<i>Information inconsistency</i>	−2.191*** (0.285)	−2.198*** (0.299)	−2.168*** (0.285)	−2.131*** (0.299)	−1.531*** (0.294)	−1.558*** (0.310)
<i>Prior exits</i> × <i>Firm volatility</i>	0.385 (0.507)	0.325 (0.492)				
<i>Prior entries</i> × <i>Firm volatility</i>	−0.346 (0.383)	−0.324 (0.366)				
<i>Prior exits</i> × <i>Market volatility</i>			−0.469*** (0.061)	−0.475*** (0.075)		
<i>Prior entries</i> × <i>Market volatility</i>			0.101*** (0.031)	0.097*** (0.035)		
<i>Prior exits</i> × <i>Information inconsistency</i>					−0.095 (0.134)	−0.117 (0.142)
<i>Prior entries</i> × <i>Information inconsistency</i>					−0.345*** (0.113)	−0.317*** (0.117)
<i>Four-firm concentration ratio</i>	0.017*** (0.004)	0.017*** (0.004)	0.021*** (0.004)	0.021*** (0.004)	0.018*** (0.004)	0.017*** (0.004)
<i>Density</i> (firms)	−0.124 (0.493)		−0.018 (0.502)		−0.043 (0.498)	
<i>Density</i> ² (firms)	−0.002 (0.111)		−0.056 (0.115)		−0.029 (0.113)	
<i>Performance as IPO proportion</i>	0.162 (0.825)	0.014 (0.848)	0.214 (0.814)	0.043 (0.855)	0.099 (0.788)	0.006 (0.819)
<i>Performance as defunct proportion</i>	1.717*** (0.404)	1.803*** (0.424)	1.580*** (0.408)	1.647*** (0.425)	1.577*** (0.419)	1.662*** (0.437)
<i>Age</i>	−0.110 (0.070)	−0.072 (0.087)	−0.110 (0.069)	−0.087 (0.084)	−0.110 (0.071)	−0.072 (0.088)
<i>Age</i> ²	0.0005 (0.001)	−0.0004 (0.002)	0.0005 (0.001)	−0.0001 (0.002)	0.0004 (0.001)	−0.0004 (0.002)
<i>Size</i>	−0.100*** (0.012)	−0.103*** (0.012)	−0.103*** (0.011)	−0.106*** (0.011)	−0.101*** (0.011)	−0.105*** (0.012)
<i>Investment preference (early stage)</i>	−0.987*** (0.200)	−0.886*** (0.203)	−1.003*** (0.198)	−0.900*** (0.203)	−1.015*** (0.203)	−0.900*** (0.208)
<i>Investment preference (late stage)</i>	−0.580*** (0.189)	−0.518*** (0.190)	−0.730*** (0.193)	−0.652*** (0.197)	−0.580*** (0.191)	−0.517*** (0.192)
<i>Public equity market</i>	0.025 (0.029)		−0.052* (0.028)		0.019 (0.029)	
<i>Constant</i>	0.205 (1.564)	−0.262 (1.482)	−0.744 (1.548)	−0.101 (1.470)	0.387 (1.568)	−0.117 (1.491)
Observations	10,790	10,790	10,790	10,790	10,790	10,790
Number of VC firms	1,342	1,342	1,342	1,342	1,342	1,342
Log-likelihood	−998.34	−980.10	−973.31	−958.47	−991.44	−974.14
Joint significance test	555.8***	29,077***	612.8***	32,466.6***	664.5***	30,549.4***
Year dummies	No	Yes	No	Yes	No	Yes

Notes. All models include duration dummies to account for time dependence in the baseline hazard rate. Robust standard errors (in parentheses) are clustered by firm.

*Significant at 10%; **significant at 5%; ***significant at 1%.

Table 4 Marginal Effect of *Prior exits* and *Prior entries* on Exit Probability at Various Levels of Firm volatility, Market volatility, and Information inconsistency

Range of moderating variable	Moderating variable					
	Firm volatility		Market volatility		Information inconsistency	
	Marginal effect of <i>Prior exits</i>	Marginal effect of <i>Prior entries</i>	Marginal effect of <i>Prior exits</i>	Marginal effect of <i>Prior entries</i>	Marginal effect of <i>Prior exits</i>	Marginal effect of <i>Prior entries</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Mean – 3 S.D.	0.033 (0.004)	–0.010 (0.002)	0.152 (0.016)	–0.043 (0.006)	0.161 (0.018)	–0.009 (0.017)
Mean – 2 S.D.	0.037 (0.004)	–0.012 (0.002)	0.122 (0.018)	–0.034 (0.006)	0.137 (0.016)	–0.022 (0.008)
Mean – 1 S.D.	0.042 (0.006)	–0.015 (0.003)	0.090 (0.010)	–0.025 (0.003)	0.098 (0.013)	–0.023 (0.003)
Mean	0.048 (0.010)	–0.017 (0.004)	0.062 (0.006)	–0.017 (0.002)	0.061 (0.007)	–0.018 (0.002)
Mean + 1 S.D.	0.054 (0.014)	–0.020 (0.005)	0.036 (0.004)	–0.011 (0.002)	0.035 (0.004)	–0.012 (0.001)
Mean + 2 S.D.	0.061 (0.020)	–0.024 (0.007)	0.019 (0.004)	–0.007 (0.002)	0.020 (0.004)	–0.007 (0.001)
Mean + 3 S.D.	0.069 (0.025)	–0.027 (0.010)	0.009 (0.003)	–0.004 (0.004)	0.011 (0.003)	–0.004 (0.001)

Notes. The marginal effects in columns (1) and (2) are based on Model 4; those in columns (3) and (4) are based on Model 6; and those in columns (5) and (6) are based on Model 8 (see Table 3). All reported values are significant at the 1% level. Standard errors (in parentheses) are determined via the Delta method.

Interaction of Market Uncertainty with Exits and Entries. Models 6 and 7 in Table 3 test Hypotheses 3A and 3B, which predict that uncertainty resulting from market volatility *reduces* the informational influence of prior entries and exits. In Model 6, we include the interaction between market volatility and both exits and entries; Model 7 adds year dummies to Model 6. Both models yield a negative and significant coefficient for the interaction of market volatility with exits and a positive and significant coefficient for its interaction with entries.⁷ Inclusion of the two interaction terms in Models 6 and 7 significantly improves the model fit compared with Models 2 and 3.

In columns (3) and (4) of Table 4, we once again report the marginal effects of *Prior exits* and *Prior entries* at various levels of *Market volatility*. These effects are calculated based on the estimates from Model 6 in Table 3. The results show that as market volatility increases, the marginal effects of both entries and exits on the focal firm's exit propensity decline monotonically in absolute terms. This finding provides support for H3: reliance on observational learning decreases with an increase in market uncertainty.

Interaction of Inference Uncertainty with Exits and Entries. Models 8 and 9 in Table 3 address Hypotheses 4A and 4B, which posit that uncertainty resulting from inconsistent information reduces the firm's reliance on observational learning. Model 8 shows the interaction

of *Information inconsistency* with *Prior Exits* as well as *Prior Entries*, and Model 9 adds year dummies.

To test Hypothesis 4, we use the coefficient estimates from Model 8 and again calculate the marginal effects of entries and exits across different levels of information inconsistency. Results are reported in columns (5) and (6) of Table 4. In line with H4, we find that as inference uncertainty increases, the marginal effect of other exits on the focal firm's exit probability declines. Our results also indicate that for values of information inconsistency ranging from two standard deviations below to three standard deviations above the mean, an increase in inference uncertainty reduces the marginal effect of entries. Only 1.6% of the observations fall outside of this range, indicating that the marginal effect of this interaction is significant and as predicted for 98.4% of the observations. We thus find support for H4, which predicts that greater inference uncertainty decreases observational learning from others' exits and entries. Finally, additional analyses (not shown) confirm that the results presented in Tables 3 and 4 are robust to the simultaneous inclusion of the three interaction terms.

Robustness Tests

We performed a variety of robustness checks to analyze the sensitivity of our findings.⁸ First, to evaluate whether the results are sensitive to our modeling choice, we reestimated the model using logit and probit specifications; our results, including estimates of the marginal effects,

remain the same. We also treated the data as if they were continuous, using a continuous-time Cox proportional hazards specification to model exit. This also did not affect the results.

Second, we tested whether exits and entries exert nonlinear effects. Organizational ecologists have documented such curvilinear effects in the context of firm founding (e.g., Delacroix and Carroll 1983), and occasionally they also expect such nonlinearity in the context of firm failure (e.g., Carroll and Hannan 1989a, b; Ingram and Inman 1996). For firm exit, it may be that only initial entries inform about opportunity, whereas additional entries imply competition. Conversely, initial exits may free resources, whereas further exits inform about hostile conditions (Hannan and Freeman 1989). The empirical evidence in terms of the significance and directional influence of these second-order effects has been inconclusive (Carroll and Hannan 1989b, Hannan and Freeman 1989, Ingram and Inman 1996), but we nonetheless included squared terms for exits and entries to allow for such curvilinear dynamics. Neither of the second-order terms was statistically significant, whereas the direction and significance of our first-order terms remained unchanged. We return to these results in our discussion.

Third, our data are left-truncated in that 5% of the sample firms were founded prior to 1980 and so were at risk of exit prior to the start of our study (Mayer and Tuma 1990). However, all our results include duration dummies for time at risk since founding. At the same time, our coefficient estimates remain stable if we restrict the sample to firms founded after 1980.

Fourth, we experimented with an alternative coding rule for the dependent variable: VC firms were coded as *exits* only if they were classified as inactive; making few, if any, new investments; or reducing investment activity. Firms classified as defunct were thus deemed as involuntary exits (failures) and coded as censored. Almost all our results can be replicated with this new coding; the only exception is the interaction effect between entries and market volatility (we find that the marginal effect of entries is attenuated for a narrower range of market volatility).

Finally, an important challenge for studies that explore observational learning is to ensure that reported effects are indeed the result of firm responses to the actions of other firms—and not the result of identical responses to a common shock (Lieberman and Asaba 2006). Our results show that recent entries and exits have an effect above and beyond the influence of common shocks (captured by year dummies and four-firm concentration and density variables), giving some assurance that exit decisions are shaped more by observational learning processes than by common resource availability. Yet as a further test, we follow the contingency approach of Shaver et al. (1997). Firms mostly observe other firms that are similar and geographically near. So if our results

are indeed driven by observational learning, then we should find that the effects of *all* entries and exits on the focal firm's exit propensity are weaker than the effects of similar and proximate others exiting and entering. Furthermore, the entries and exits of VC firms that are geographically distant and have a different investment focus should be discounted as mostly irrelevant to the focal firm's exit decision. Of course, such patterns should *not* be evident if firm exit decisions are identical responses to a common shock. We find that aggregating prior entries across geography and investment preferences does not affect the focal firm's exit decision. Aggregate prior exits do have an effect, but it is only a third of the effect exerted by similar and proximate others exiting. Next, we took aggregated exits and categorized them either as exits by similar and proximate VCs or as exits by dissimilar and distant VCs; we followed an analogous procedure for entries. We find that (i) exits and entries by similar and proximate VCs have the hypothesized effects, and (ii) the effects of exits and entries by dissimilar VCs are insignificant. Overall, then, these patterns are consistent with observational learning as a key driver of our findings; they are also largely incompatible with our results being driven by identical firm responses to a common shock.

Discussion

Our study investigates the effects of different uncertainty types on imitation in firm exit decisions. In line with previous findings on the influence of firm uncertainty (Belderbos et al. 2011; Henisz and Delios 2001, 2004), we find that uncertainty stemming from volatility in a focal firm's performance increases its tendency to imitate. In contrast, the uncertainty stemming from volatile markets has an effect on every firm's decision making. We depart from previous conceptualizations (Henisz and Delios 2004) to postulate and to demonstrate that market uncertainty reduces imitation. Understanding this result requires that we consider *why* firms engage in observational learning: because they view the actions of other firms as informative for their own decision making. But any uncertainty that affects the decision making of all firms makes it doubtful that others' actions are indeed informative, thereby dampening imitation. Finally, imitation is further reduced if the actions of others do not allow for consistent inferences. Taken together, these findings have implications for the study of imitation in institutional theory, herding models, and organizational ecology. They further contribute to discussions on conceptualizing firm exit as a decision problem rather than an inevitable consequence of firm failure.

Implications for Institutional Theory

Institutional theory has had a long-standing interest in organizational responses to uncertainty (e.g., DiMaggio 1988, Goodrick and Salancik 1996, Meyer and Rowan 1977). DiMaggio and Powell (1983) argue that mimetic

isomorphism (as distinct from normative and coercive isomorphism) in particular is a standard response to uncertainty. Cognitive legitimacy, which is expressed in shared frameworks of interpretation, is then the result of mimicking other organizations' behaviors that are understood to be common and appropriate (Deephouse and Suchman 2008, DiMaggio and Powell 1991, Scott 2001). This consideration results in an interesting observation for us: the concepts of cognitive legitimacy and observational learning share a fundamental feature in that they both stress the influence of others' observed behaviors on a focal firm's actions. However, predictions on the role of uncertainty in this relationship seem to differ: whereas we argue that some uncertainty types decrease imitation as driven by observational learning, institutional theory generally views uncertainty to increase imitation as driven by firms' quest for cognitive legitimacy.

To resolve this apparent contradiction, it is helpful to trace the origins of institutional theory's notion that uncertainty increases isomorphism and to highlight how this original idea has been qualified over time. There has been a traditional dichotomy in institutional theory between technical considerations and institutional forces (Goodrick and Salancik 1996, Lounsbury 2008). Along with this dichotomy, the emphasis was mainly on showing how institutional processes (such as mimetic isomorphism) help resolve the uncertainty inherent in poorly understood technologies (Meyer and Rowan 1977). Over time, this idea was interpreted to apply more generally, despite limited explicit explorations of how different uncertainty types may shape imitation and conformity. However, in subsequent statements, scholars have redressed this "overdrawn dichotomy" between technical and institutional processes (Goodrick and Salancik 1996, p. 25) and reiterated that technical considerations are often institutionally embedded (Barley and Tolbert 1997, Lounsbury 2008). This suggests that uncertainty and mimetic isomorphism may interrelate in a more nuanced manner than implied in the broad interpretation of the original idea.

Recent research on conflicting institutional logics, especially in the context of emerging fields, provides a case in point (Navis and Glynn 2010, Purdy and Gray 2009). This research suggests that in such fields, institutional arrangements themselves can exhibit considerable levels of uncertainty. There is a growing interest in understanding how firms respond to such institutional uncertainty (Greenwood et al. 2011). Because there is considerable ambivalence about what to mimic, a "probabilistic, rather than a deterministic[,] view of adherence to dominant norms of behavior" is perhaps more appropriate (Thornton and Ocasio 2008, p. 106). One notion is that institutional uncertainty can create room for firms to strategically pursue their individual interests (Gaba and Bhattacharya 2012, Goodrick and Salancik 1996, Kraatz and Block 2008, Oliver 1991). In

that sense, uncertainty then does not always foster imitation and conformance. However, the emphasis on strategic maneuvering and the resources that firms employ to exploit this uncertainty directs attention away from exploring how firms might actually attend to and process uncertain or conflicting institutional logics, and how it may be this process itself that reduces isomorphism.

Although we have anchored our study in observational learning, rather than institutional theory, our findings can speak to this. Our findings imply that it need not be strategic interests that reduce imitation in the face of certain types of uncertainty; instead, it may simply be that firms purposefully reduce their reliance on imitating others because it is unclear whether others' actions are informative about what might be legitimate. Variations in behaviors—the "loss in isomorphism"—may thus result from inferential difficulties and not just from variations in firms' strategic interests. The study by Rhee et al. (2006) provides powerful evidence to this end. Rhee et al. show that mimetic isomorphism is dampened when either high variance in the behavior of imitation targets or small sample sizes create uncertainty over which exact behavior is seen as legitimate.

Our findings then underscore two important ideas: First, to arrive at a more comprehensive understanding of how uncertainty drives isomorphism, it is critical to specify the various uncertainty types at play. It appears that different uncertainty types can differentially affect firm imitation, a concept that gets lost when a general notion of uncertainty is employed. Second, these findings call for further exploration of the exact processes that underlie mimetic isomorphism. Our results suggest that imitation, as driven by observational learning, entails a considerable level of deliberateness. Because institutional pressures were unlikely to play a role in our findings, we cannot directly extend these findings to suggest that a similar deliberateness will also be present in imitation stemming from legitimacy pressures. Yet our findings are in line with a number of institutional theorists that have sought to correct the idea of an "a-rational mimicry" process (Lounsbury 2008, p. 350) that views isomorphism as a result of firms reflexively and unconditionally imitating each other (Mizruchi and Fein 1999). Rather than viewing imitation as mindless and structurally determined, these scholars suggest that it is better understood as a complex interpretive process (Strang and Still 2006) and as an effortful accomplishment (Lounsbury 2008).

Overall, then, our study highlights an area in institutional theory where important aspects remain to be understood. Specifically, it seems that few institutional accounts have explored how exactly firms experience isomorphic pressures, interpret them, and learn to manage them over time. Our study, along with studies such as Rhee et al. (2006), emphasizes the decision-making processes in the focal firm and, as such, begins to

develop the necessary link in the causal chain connecting abstract isomorphic pressures to concrete organizational responses.

Implications for Herding Models

Our study also contributes to the herding literature. First, an important line of inquiry in herding models examines how shocks can slow imitation and dislodge informational cascades. Scholars have identified possible shocks, including the release of new public information, shifts in the underlying value of adopting versus rejecting the behavior in question, and the overconfidence of decision makers in their private information (Bikhchandani et al. 1998, Hirshleifer and Teoh 2003, Nöth and Weber 2003). We add to this line of inquiry by identifying empirically yet another shock that, in a sense, is the flipside to overconfidence in private information. In particular, we show that imitation also slows when decision makers lack confidence in others' information (in our case, this is due to market uncertainty). Note, however, that a lack of confidence in others' information is not just an inseparable counterpart to overconfidence in one's private information so that one effect would imply the other. Instead, in our study the lack of confidence in others' information equally extends to the focal firm's information. Future research may explore the secondary consequences of this. If firms lack confidence both in their own and others' information, where and how do they gather the information needed for their decision making? For imitation among banks, Strang and Still (2006) find that decision makers turn to consultants and academics. However, the relevance of these players may vary across settings or firms may alternatively respond by delaying their decisions altogether.

Second, herding models conceptualize decision makers to infer information not only from predecessors that adopt the behavior in question but also from predecessors that reject that behavior (Banerjee 1992, Bikhchandani et al. 1992). Most empirical studies that invoke observational learning, however, do not consider the informational influences of others that reject or abandon the target behavior. For example, Greve (1995) and Rao et al. (2001) view decision makers as deciding to discontinue a practice based partly on information inferred from others discontinuing, yet they do not consider that information can also be inferred from decision makers initiating (or choosing to continue) the practice. Recent conceptual work (Terlaak and Gong 2008) and empirical studies have begun to rectify this; Greve (2011), Xia et al. (2008), and Connelly et al. (2011) all show that in the context of adoption, firms attend not only to adopters but also to abandoners and rejecters. Our study further supports this—we find that in the context of firm exit decisions, firms infer information from both exits and entries. We also take the next step in this line of inquiry: if firms attend to both adopters

(exits) and rejecters (entries), how do they respond to the inconsistency in revealed information? We show that the higher this inconsistency, the smaller the reliance on this information. Future research might explore whether this response is universal or bounded by certain conditions. For example, firms may sort through inconsistent information by assigning different weights to different information sources (Greve 2011), a response similar to that used for information that is heterogeneous (e.g., Greve 1998, Kim and Miner 2007).

Implications for Organizational Ecology

Our focus on imitation in the context of firm exit also has implications for studies in organizational ecology. Scholars drawing on population dynamics commonly invoke imitation in the context of firm *entry* (e.g., Delacroix and Carroll 1983, Haveman 1993), where prior entries and exits shape subsequent entries via an information effect and a resource effect. Initial entrants exert an informational influence by sending feasibility signals to potential entrants, thereby triggering more entries; in contrast, later entrants have a resource effect because they are indicators of competition and crowding out, which discourages additional entries. Conversely, initial exits have a resource effect whereby freed resources entice new entries; however, the effect of later exits is informational because they are indicators of a difficult environment, which inhibits potential entrants (Delacroix and Carroll 1983).

Organizational ecologists less frequently expect prior exits (and entries) to exert a parallel curvilinear effect on firm *exit* (see Baum and Shipilov 2006 for a comprehensive review). Instead, exits are mostly presumed to reduce subsequent exit in a linear way via freeing up resources that can be recycled by incumbents (Baum and Oliver 1992, Delacroix et al. 1989, Wade et al. 1998). Where scholars have considered exits (and entries) to shape subsequent firm exit in a curvilinear fashion, results have been inconclusive (Carroll and Hannan 1989b, Hannan and Freeman 1989, Ingram and Inman 1996). In addition, the potential informational influence of prior exits, if any, has been conceptualized to operate indirectly through affecting external organizations that control resource flows into the focal industry (Hannan and Freeman 1989). High exit rates “make it difficult for members of a population to convince those who control resources in the environment to continue flows of essential resources” (Hannan and Freeman 1989, p. 142), which, in turn, increases the failure rates of industry firms. In contrast, in our study, we theorize and find that focal industry firms also attend to and act on the information revealed by prior firm exits (and entries).

The expectation that exits (and entries) primarily shape subsequent firm exit via a resource release effect, and the notion that an informational effect operates at all, is indirectly consistent with organizational ecology's

view of firm exit as deterministic. Indeed, many studies in organizational ecology focus on industries with large, capital-intensive firms that have high fixed costs in terms of expensive and highly specialized equipment—e.g., semiconductor firms (Freeman 1990), breweries (Carroll and Swaminathan 1991), newspapers (Hannan and Freeman 1989), and wineries (Delacroix et al. 1989). These fixed costs can be barriers to exit, making it less reasonable to view exit as a decision problem that is subject to the direct informational influences of prior exits and entries. Yet at the same time, organizational ecologists argue that not all industries will allow for resource recycling (so that the resource release effect is muted) (Delacroix et al. 1989) and, further, that conceptualizing firm exit as firm failure can be too restrictive. As Carroll and Delacroix (1982, p. 170) note, “Not all deaths are the result of performance failure,” and so observing a firm’s exit need “not logically imply anything about its . . . performance.” For organizational ecology, this suggests that perhaps some of the inconclusive findings in population dynamics (see Baum and Shipilov 2006) may be resolved by conceptualizing, where appropriate, firm exits as a decision problem. In fact, when studying the dissolution of accounting firms, Pennings et al. (1998) find that prior exits *increase* subsequent exits—a result that was unexpected for them and difficult to reconcile with the notion that prior exits dominantly exert a resource effect. It is in line with our results, however, and readily understood if we view prior exits to also exert an informational influence. Indeed, accounting firms (such as VC firms) are both human capital intensive and small (in the Pennings et al. 1998 study, the average firm employed 3.4 accountants) and thus meet the conditions under which firm exits can be conceptualized as a decision problem subject to informational influences.

Generalizability of Our Conclusions

Discussing the generalizability of our study requires considering (1) whether our theory of observational learning in firm exit is applicable to other exit settings and (2) whether it is generalizable to contexts other than firm exits. The first consideration calls for some additional thoughts on viewing firm exit as a decision problem, a point that we already explore above in the context of organizational ecology. To be sure, our theory only applies when exits can rightfully be seen as voluntary. Yet this may limit our theory’s generalizability less than it appears at first sight. This is because scholars are increasingly suggesting that the conventional view of firm exit as involuntary failures that occur as unfit firms succumb to economic, ecological, and technological selection pressures (Anderson and Tushman 2001, Carroll and Hannan 2000, Klepper and Graddy 1990) may not be universally applicable (Baker and Nelson 2005, Gimeno et al. 1997, McGrath 2006,

van Witteloostuijn 1998, Wennberg et al. 2010). Pointing to successful firms that exit markets (Bates 2005, Caves 1998) and poorly performing firms that remain in markets (van Witteloostuijn 1998), these scholars suggest that a more nuanced and inclusive conceptualization of firm exit is in order. For instance, idiosyncratic judgments of what constitutes “failure” can be one factor that infuses a decision flavor into many exit situations. Consider that an entrepreneurial venture may be terminated as its actual or anticipated performance drops below a critical threshold, with this threshold entailing a subject assessment of alternatives (Gimeno et al. 1997). Entrepreneurs may thus disband an economically viable business if other activities appear more lucrative, their interests change, or anticipated growth is limited. In contrast, poorly performing firms may be buffered by institutional linkages (Baum and Oliver 1991) or sustained by self-interested stakeholders, resulting in “permanently failing” underachieving organizations (Meyer and Zucker 1989).

Of course, this is not to suggest that economic, ecological, and technological selection pressures do not matter in these cases. Instead, together these studies suggest that these pressures may work *in tandem* with an element of choice to shape firm exits. Put differently, it may not be just selection pressures that matter or just choice that matters. Instead, both elements likely are important, and whereas the balance of them can vary across settings, it may be, in fact, the exception that just one element exclusively matters. If so, universally equating firm exit with firm failure unnecessarily limits our understanding of this phenomenon. We have shown that if we allow for choice, together with selection pressures, to enter into the exit equation, exit is also shaped by the informational influences of others. This finding is conditioned on the importance of the choice element in our context, but it nonetheless underscores the more general point that a greater conceptual clarity around the notion of choice in firm exit can result in a richer, more complete understanding of this phenomenon.

The second consideration in terms of generalizability pertains to the broader applicability of our theory to contexts other than firm exits. We posit that this generalizability is given, as long as three criteria are present—that the behavior or action at hand can be viewed as a decision problem, that this problem is surrounded by different types of uncertainty, and that decision makers are boundedly rational. A broad range of decisions meet these criteria not only in the context of firms adopting new technologies, strategies, market positions, and practices but also in the context of firms discontinuing or abandoning these innovations. Indeed, not surprisingly, these are all decision problems that scholars have examined using theories akin to the one we have employed here—theories of imitation, social learning, contagion, and informational influence (e.g., Gaba and Meyer 2008;

Greve 1995, 2011; Haunschild and Miner 1997; Rao et al. 2001; Terlaak and King 2007). We thus expect that further insights will emerge when applying our theory to these settings, especially with respect to the differential effects of different uncertainty types. Yet one word of caution is warranted when taking our theory outside the context of firm exit: although our choice of firm exit as the research setting came with a set of challenges (as we discuss above), it did come with the distinct advantage that it reduced the potential for imitation to result from factors other than observational learning, including normative or cognitive conformity pressures. In contexts other than firm exits, these conformity pressures are likely to operate alongside observational learning processes. This, in turn, would require scholars to both isolate the influence of each process and account for their potential interactions.

Limitations

Finally, our study is not without limitations. First, we do not account for firms' post-exit activities. Given the nature of our dependent variable, this limitation is embedded in the phenomenon under study and thus is common to studies of firm exit. Nonetheless, we randomly chose 200 VC firms that exited our sample to check for any systematic post-exit activities (e.g., immediate reentry) that might conflict with our theoretical exposition; no evidence of such activities was found. We could trace some VC firms that redeployed their talents in a different industry (as when New South Ventures switched its focus to create the software company Guardian Solutions). A few others were acquired, but unlike in other settings where the acquired firm continues to exist under the buyer, acquired VC firms truly exited, with general partners leaving and the acquirer simply purchasing the interests of its target (as when Horn Ventures acquired the interests of the general partners of W. R. Grace Venture Capital).

Second, although we control for the usual factors (besides observational learning) that affect exit—for example, firm performance, ecological dynamics, and macroeconomic conditions—it may be that other factors (for which we could not account) also influence exit decisions. To gain a grip on this possibility, we interviewed exiting and former VC firms. Informants confirmed that many factors shape exit decisions, including long working hours and personality clashes among the partners. Yet because there is no evidence of these factors having a systematic effect on our data, they are more likely to introduce random noise into the analysis than to bias our results.

Conclusion

Viewing uncertainty as a general condition fostering imitation disregards that, in many cases, uncertainty does

not simply act as an amorphous force. We show that once we decompose uncertainty into different types and shift the focus to decision-making processes of organizations, different uncertainty types differentially affect imitation. These findings open up exciting avenues for more nuanced explorations of the interplay between uncertainty and imitation, and we hope that they encourage future research to develop greater conceptual clarity around the notions of choice and deliberation in imitation processes.

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Endnotes

¹Research on survival-enhancing learning also examines firm failures; it theorizes that exits are related to cumulative prior exits because firms can learn from the evidence of historical failures, which may reduce their own failure rates (Ingram and Baum 1997, Kim and Miner 2007). Like organizational ecology, and unlike our study, this research stream thus views exits as failures and proposes a negative relationship between prior and subsequent exits.

²A main point of herding models is to show that this expectation can be incorrect, especially if decision makers are part of an informational cascade (an extreme form of observational learning where decision makers exclusively act on information inferred from others, in complete disregard of their private information) (Hirshleifer and Teoh 2003).

³For 98% of the sample, the entry date coincides with the year of first investment. For the remaining 2% (32 firms), we confirmed entry dates by making Internet searches.

⁴The variance inflation factors for *Density* and *Density*² each exceed 10; this indicates that multicollinearity is high, which may preclude identifying estimates with precision (see Gunst 1983).

⁵Results are shown for the firm volatility measure that is based on the proportion of ventures that went IPO. The alternative volatility measure (based on the proportion of defunct ventures) neither affected the probability of exit nor moderated the effects of prior entries and exits; moreover, including this alternative volatility measure as an additional control did not affect our main results. We therefore excluded it from the analysis.

⁶Standard *t*-tests comparing the equality of the marginal effects reported in Table 4 *reject* that any two of the marginal effects in column (1) are equal to one another. That is, the increase in the marginal effect of exits as volatility in firm performance increases is statistically significant. The same is true for the other columns.

⁷With year dummies, interaction terms can be identified, whereas the stand-alone term *Market volatility* cannot.

⁸Results are available from the authors upon request.

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