The Non-consensus Entrepreneur: Organizational Responses to Vital Events*

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Abstract

Salient successes and failures, such as spectacular venture capital investments or agonizing bankruptcies, affect collective beliefs about the viability of particular markets. We argue that collective sense-making in the wake of such vital events results in consensus behavior among entrepreneurs. Market search is a critical part of the entrepreneurial process, where entrepreneurs frequently enter new markets to find a high-growth area. Keying on vital events, entrepreneurial firms flood into markets that have experienced salient successes, but they stay clear of those with recent failures. Like entrepreneurs, venture capitalists also exhibit herding behavior, following other VCs into hot markets. We theorize that vital events effectively change the selection threshold for market entries, which changes the average viability of new entrants. Consensus entrants are predicted to be less viable, while non-consensus entrants are predicted to prosper. We find empirical support for the theory among software startups. The non-consensus entrepreneurs that buck the trend are most likely to stay in the market, receive funding, and ultimately go public.
Entrepreneurship has intrigued and perplexed social scientists. Many scholars look at the conditions that give rise to entrepreneurship (Baumol, 1996; Ruef, 2010), including economic opportunity, social context, and geographic place (Shane and Cable, 2002; Klepper, 2007; Sørensen, 2007; Powell, Packalen, and Whittington, 2012). One line of inquiry focuses on what leads individuals to create new firms (Evans and Jovanovic, 1989; Stuart and Sorenson, 2005; Lazear, 2010). But much interest in entrepreneurship surrounds how upstart firms change the economic landscape (Schumpeter, 1934; Aldrich and Fiol, 1994; Venkataraman, 1997).

Entrepreneurship is often characterized by dramatic boom and bust cycles, with producers, financiers, suppliers, and pundits looking to one another for cues about what are the most promising new areas (Bikhchandani, Hirshleifer, and Welch, 1998; Jovanovic, 2009). High-profile successes in a market can trigger waves of entry, while high-profile failures render a market untouchable.

The nature of these organizing waves remains the subject of public debate and academic research. Much of the focus is on what drives booms and busts. Some studies suggest that entrepreneurial waves result from social factors (Ruef, 2006; Sine and David, 2010; Aldrich, 2011). Other researchers explain herding into and out of markets as evidence of decision biases (Camerer and Lovallo, 1999; Kahneman, 2011). Regardless of their sources, these cycles present a challenging terrain for entrepreneurs. But researchers have paid less attention to the consequences of how entrepreneurs navigate these environments.

Our interest is in perhaps the least celebrated of entrepreneurial events: market entries that move against consensus views. We define consensus behavior as that which follows prevailing beliefs in the market, and non-consensus actions as those that counter common wisdom. Non-consensus entrepreneurs resist the temptation to herd into markets made popular
by high-profile successes, and may enter markets that have been tainted by failures. In uncertain contexts, such nonconformity may seem especially high risk: institutional research describes the importance of entrepreneurs framing their actions as consistent with mainstream beliefs (Lounsbury and Glynn, 2001; Martens, Jennings, and Jennings, 2007; Aldrich and Martinez, 2015). Our model suggests a different perspective. We use selection reasoning to theorize about herding in the wake of vital events, and propose that conforming to the consensus view is detrimental, while there are advantages to non-consensus behavior.

We conceive of market entry as a selection process. In our model, high-profile successes and failures lead to different levels of scrutiny in the decision to enter a market. When spectacular financings result in a collective overstatement of the attractiveness of a market, a consensus emerges that the market is resource-rich and the path is cleared for many entries – including those that do not have a clear fit. The barrier to market entry is effectively lowered. And when notorious failures render a market unpopular, only the most viable entrants will overcome exaggerated skepticism and enter, taking the non-consensus route.

Drawing on interviews we conducted with entrepreneurs and venture capitalists (VCs), as well as popular and academic literature, we argue that a critical part of entrepreneurship is the process of market search.1 Entrepreneurs start with an idea, a technology, or an early-stage product, and, after founding the firm, engage in a search process to find a market category in which their firm can gain traction and dominate.2 They enter market categories as a “restart,” introducing a new product, or as a “pivot,” shifting an existing product in a new direction. We argue that vital events–high-profile success and failures–are important social cues that influence

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1 The definition of “entrepreneurship” ranges from any transition into self-employment, to founding a “Main Street” business, to founding what is intended to become a high-value firm (Ruef, 2010; Stuart and Sorenson, 2005). Our focus is on the latter. We refer to the team running an entrepreneurial firm as “entrepreneurs.”

2 We draw on the view of markets and sub-markets as categorical systems that group organizations and products (Sujan, 1985; Porac and Thomas, 1990; Hannan et al., 2007; Pontikes and Barnett, 2015).
entrepreneurs’ decisions to enter a market category. But that is not the end of the story. There are enduring consequences to a consensus or non-consensus response to these cues, where non-consensus entrepreneurs realize more favorable outcomes.

To investigate these ideas, we look at software entrepreneurs. The software industry is characterized by many market categories, or sub-markets, that segment the domain. There are over 400 market categories in the software industry during our study period, from 1990 through 2002. We study consensus behavior by looking at how positive and negative vital events affect entry into market categories. We then investigate long-term consequences of consensus and non-consensus entry in terms of market exit, receiving financing, and going public.

**Entrepreneurial Search**

Search is central to the entrepreneurial process. In his influential management book *The Four Steps to the Epiphany*, Steve Blank provides the following advice to entrepreneurs who are not gaining market traction: “before changing the product, you need to keep looking for a market where it might fit. If, and only if, you cannot find any market for the product do you discuss changing the feature list,” (p. 89). Common wisdom in the tech industry claims that this “painful, soul-searching” process (p. 89) is critical for entrepreneurial success (Ries, 2011; Blank, 2013). The popularity of these books indicates that entrepreneurs subscribe to this idea.

Our interviews reinforce this view, suggesting that entrepreneurs actively engage in market search. As one venture capitalist states, “if you built a product and it’s not catching market traction, you take your high-quality team and idea and look for another market to pursue.” S/he describes the process:

You’ve spent somewhere between 4-6 quarters on your original business plan and you can’t get product-market fit. … that’s the point at which an entrepreneur and his or her board and investors start to say, hey this thing’s not working. We need to consider other options … the entrepreneur
will come to the investors – or the investor will go to the entrepreneur, and say, it’s not working, what else you got? And they’ll start a process by which they explore other new ideas and tinker with them a little bit, get feedback from people. And if one looks like it’s promising they might build that and launch it.

Another venture capitalist stipulates stages in a firm’s search for a market category it can dominate:

[Companies] traverse these different transitions … if you get stuck in technology, then you’re a technology in search of a problem; if you’re a product and not quite a company, then you’re a feature … if you’re a company but never really figure out market power, then you’re either the Main Street business or you’re traction, [but] not a category king.

An entrepreneur adds, “I think [market entry] happens pretty frequently, especially at early stage companies. I think at every company that I’ve worked at we’ve entered new markets, and I haven’t worked at a company for more than 4-5 years.” Firms typically engage in market search when they are struggling. But that does not mean that entrepreneurs who search are unsuccessful. Many prominent entrepreneurs achieve success by engaging in a productive process of market search.

For example, the ridesharing company Lyft was initially called Zimride and sold technological platforms that facilitated carpooling to companies. It then shifted to selling long-distance rides to individuals. Finally, it built a mobile application that created a network between customers and drivers, a move that required major changes to both the technology and the business model. Renamed Lyft, they spun off the Zimride business. Instagram was initially a location-sharing product that competed with Foursquare; it evolved into a networked photo-sharing product with filters. Groupon transformed from a community-organizing platform to a group-transaction local deals site. Wealthfront, an automated investment service that allows customers to invest with professional managers, was founded as an investment game where amateur investors would compete. As these examples indicate, market search does not mean entrepreneurs discard what they have and start anew. Rather, they build on their past
developments, using existing products, technologies, or market insights as a starting point to search for a market category where the firm can gain traction.

This search process is resonant with the literature on organizational change. Levinthal and March (1981) propose a model of adaptive learning where organizations search for new technologies when performance falls below aspiration levels, and the opportunities sampled depend on the current technology. White (1981) argues that producers position themselves in a market in response to the actions of competitors. According to Weick (1979), organizations change through a path-dependent process where managers scan environments, selectively choose information, and make sense of it using existing schemas. Entrepreneurs are managers of start-up organizations who employ these behaviors when they engage in market search.

Using our data, we can systematically investigate the frequency of entrepreneurial search. We find that software entrepreneurs enter new market categories every other year on average, with the top 30% entering new market categories yearly.\(^3\) This pattern corroborates the narrative put forth in the management literature and from our interviews. It is not that a company stays in the market in which it is founded, and either thrives in that market or fails. Instead, part of entrepreneurial strategy is to search for a market where the company’s products will be well received.

**Entrepreneurial Waves**

Many theories of entrepreneurship depict individual entrepreneurs making isolated decisions, akin to a lone scientist tinkering in a laboratory. But an entrepreneur is not an isolated inventor; she is creating an organization where multiple people need to agree on a course of

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\(^3\) These statistics are reported on organizations that appear for more than one year.
action before it is taken (Ruef, 2010). All of our interviews describe investors, board members, and executives deciding whether to enter a new market. As an entrepreneur describes:

I would say we moved [to the “platform” category] slowly. [We first established that] we [can] build a product that makes sense. OK … that’s great. Can we sell it? Oh, look, we sold it once. And then it was really a discussion at the board level. Hey, … we are now selling this product … at 8-10x our other contract values – we’re going to continue to push it. Then it really took another year. … Literally [the board] had a debate, why should we bother investing in [our current market], if this is really sellable, and it’s ultimately not any more work? It was somewhat just theoretical … because of course we weren’t going to hang up [the current market], but it took another year before that really got legs. So is that slow? Probably.

In addition to getting internal constituencies on board, entrepreneurs also weigh how investors might view the move. Start-ups are financed in stages, so entrepreneurs try to position the company to continue to attract investment at good terms. As such, the expected preferences of potential investors are also taken into account.

It is easier for internal and external actors to agree that entering a market category is a wise course of action if there is a broader consensus in the industry that the market under consideration is attractive. The viability of the market is seen as central to a company’s prospects—more important than the management team (Kaplan, Sensoy, and Strömberg, 2009) or even the underlying technology. This point was underscored in every interview we conducted. One venture capitalist summarized, “If you are in a bad market, it doesn’t matter how good your team or your technology is. It doesn’t matter.”

Anticipating this scrutiny, entrepreneurs heavily weigh whether a market is poised for growth. This judgement is influenced by whether others outside the company—especially highly regarded individuals—believe that the market category is “hot.” One entrepreneur states, “The big thing for [our company] is that the market potential in this new market is much, much bigger than [the old market].” Another says the potential of the market was a stronger driver of entry than the company’s technology or other capabilities: “At [company], we made that shift not because of technology reasons, but because that was where the market was. It was very much a
market decision.” Even an entrepreneur whose firm had not pivoted described the temptation to enter a faddish market:

One of the times we were really close to jumping on a bandwagon, was in the earlier days of … that whole trend of Facebook page management. ... and we had an off-site strategy discussion about it, [saying] look, we’re already in so many of these retailer’s brands. These guys aren’t competitive but they’ve come up with something that maybe we could upsell. We did a market sizing analysis on it, and ultimately decided the market wasn’t big enough and didn’t enter it. And we were ultimately right. … but we very much considered going into the hot market. By doing our own analysis on it and trying to decide, [we came] to the conclusion that it wasn’t really that big.

When engaging in market search, entrepreneurial teams try to make sense of market categories in a domain, looking for markets with high potential. We think this group sense-making leads to consensus behavior. Because of the uncertainty inherent in evaluating markets, people look toward others for social cues, a tendency that is exacerbated in collective decision-making (Janis, 1982). As a result, firms follow each other into markets. Such herding behavior has been found in many contexts (Delacroix and Carroll, 1983; Haveman, 1993; Davis, 1991; Greve, 1996; Carroll and Hannan, 2000; Rao, Greve, and Davis, 2001; Sørensen, 2007; Sørensen and Sorenson, 2003; Yue, 2012). One organization’s experience provides information to entrepreneurs who follow (Scharfstein and Stein, 1990; Miner and Haunschild, 1995; Dosi and Lovallo, 1997; Aldrich and Ruef, 2006). This feedback process often magnifies, rather than corrects, distortions, resulting in exaggerated perceptions of the promise or peril of a market category. The net result is entrepreneurial waves, long observed by social and economic historians (Kondratieff, 1935; Schumpeter, 1939; Polanyi, 1944). Waves of entry reflect consensus views: perceptions–or misperceptions–that particular markets have high or low potential.
The Role of Vital Events

Much of the literature on entrepreneurial waves depicts entrepreneurs following each other. We think it is also important to consider the catalyzing role of vital events. Salient positive or negative events are covered by industry media and widely discussed. Vital events are an actual or perceived indicator of the underlying quality of a market that help define the consensus view. Managers evaluating the viability of markets will take note. Even one vital event may exert influence, particularly when limited information is available (Levinthal and March, 1993).

Denrell and March (2001) show that in sequential sampling, successful behaviors are repeated and unsuccessful ones avoided. As a result, a few vital events can have an exaggerated effect on market assessments. A high-profile financing may trigger an explosion of interest in a particular market category, as we see in the eruption of fads and fashions (Strang and Macy, 2001). Bankruptcy, perhaps the most salient negative event for a business, elicits strong negative reactions (Sutton and Callahan, 1987). Positive and negative vital events serve as powerful indicators of the (apparent) wisdom or folly of positioning in a particular market category.

Even if vital events are initially based on differences in quality among markets, the buzz generated through comparisons among markets will create exaggerated assessments. Individuals and organizations imitate high-status others (Burt, 1987; Davis, 1991), especially under conditions of uncertainty (Festinger, 1954; Kahneman, 2011). Meanwhile, people who are disposed to question whether a vital event is diagnostic may be unlikely to express this deviant view (Miller and Morrison, 2009). For example, one VC we interviewed described having repeatedly to defend their firm’s decision not to invest in what was considered a “hot” market category:

… you look at the unit economics [of the market], … and you just can’t possibly … make sense of [it]. All of that stuff, we don’t understand. I’ve never made a bet on it … I’m always talking to
people about the fact that I must have missed something because people have clearly found something in this.

Many investors or entrepreneurs might avoid speaking up rather than having to engage in such contentious conversations. This leads the perception of the consensus view to become exaggerated—more positive or negative than is warranted given the underlying quality of the market.

In our interviews, we frequently heard references to vital events changing appraisals of a market. One entrepreneur explains:

> We track [VC investment] a lot … we watch it closely. Anything similar to us, we watch for acquisitions, we watch for the pricing. … It’s useful for understanding where we should be valued so we’re able to … keep a constant eye on should we move in this direction, or that direction, a bit, strategically. Because ultimately we’re trying to optimize investor value, and we have to understand where the market is putting their money.

Another of our interviewees, a venture capitalist, noted that a few negative vital events stigmatized the “flash sales” market:

> Flash sales is another area – kind of untouchable. Because, not only did Gilt have a huge problem with their business model, Zulily went public but afterward kind of crashed and burned. The whole flash sales model is a little untouchable, nobody really wants to go there.

In sum, vital events are an indicator of a market’s potential that are widely broadcast and discussed. From them, a general industry consensus develops about the promise or peril of a market. This drives exaggerated perceptions about how easy or hard it will be for a firm to succeed in the market.

As a result, we expect vital events to influence market entry. Entrepreneurs seek to enter markets that have high potential. Convincing stakeholders that a company should enter a market category requires constructing a narrative that draws on what people understand and value (Aldrich and Fiol, 1994). Such narratives employ existing cultural toolkits, where entrepreneurs construct stories that align with people’s normative beliefs (Rao, 1994; Lounsbury and Glynn, 2001; Martens, Jennings, and Jennings, 2007). A narrative is more compelling if it draws on
common perceptions of value. For the first stage of our model, we propose that entrepreneurs follow consensus views in entering markets. Thus we expect vital events to generate exuberance and skepticism in market entry.

Hypothesis 1a: The greater the number of positive (negative) vital events in a market category, the greater (lower) the ensuing hazard of organizational entry into that market.

Entrepreneurs are not the only audience affected by consensus perceptions. Venture capitalists are also susceptible to influence. Although there is a widespread belief that VCs are better than other investors at identifying winning opportunities, research shows that this is typically not the case. Returns to VC investments are dramatically skewed, with a minority of VC firms reaping the majority of returns through the IPO process (Gompers and Lerner, 2001). It is not even clear whether VC investments, on average, generate returns that are better than public financial markets (Harris, Jenkinson, and Kaplan, 2014). VCs face considerable uncertainty in evaluating the promise of a potential investment. This may explain the strong social comparisons that have been observed among VC firms (Sorenson and Stuart, 2008).

Consequently, we expect VCs will also be influenced by consensus views in the wake of positive vital events. VCs see each other’s investments as important information that indicates a market in which they, too, should be investing. The tendency of venture capitalists to invest in companies that are in “hot markets [with] hyped business models” has been cited as a factor that led to the Internet bubble and its subsequent collapse (Valliere and Peterson, 2004). As one venture capitalist stated, “You don’t want to miss out on something hot. So, if everyone agrees the sector is hot, we have to pay the going rate to get into it” (Valliere and Peterson, 2004, p. 16).
Our interviews also support this view. Both VCs and entrepreneurs commented that herding behavior was rampant among VC investors (although each described their own firms as avoiding consensus behavior). If our arguments are correct, then VCs also follow vital events.

Hypothesis 1b: The greater the number of positive vital events in a market, the greater the ensuing hazard of an organization in that market receiving venture capital financing.

Entry Selection and the “Non-consensus Entrepreneur”

So far, we have drawn on a large body of research and interviews to argue that vital events predict market entry and VC financing. We think an equally pressing—but less studied—question asks what are the consequences of consensus or non-consensus entry. Drawing on the idea that entry into a market can be understood as a selection process (Barnett et al., 2003), we propose that it is possible to predict the viability of entrants based on consensus or non-consensus entry. This is in line with findings from previous studies, where people who follow fads are more likely to abandon their positions (Rao, Greve, and Davis, 2001; Yue, 2012), and organizations founded—or funded—in boom times are more likely to fail (Barnett et al., 2003; Nanda and Rhodes-Kropf, 2013). In the first stage of our model, both entrepreneurs and VCs follow vital events into markets. In the second stage, we argue that when a consensus develops that a market is high potential, it lowers the selection threshold for market entry. This results in hazardous long-term effects. We focus on three outcomes: market exit, receiving VC funding, and going public.

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4 Nanda and Rhodes-Kropf (2013) argue that this result is due to variance, rather than mean effects, in the selection process. We discuss our results in light of their findings below.
Central to our model is that the consensus view of a market category affects how difficult it is to enter the market: in terms of how easily managers can imagine the organization will succeed, the extent to which decision makers will accept imprecise explanations about market fit, and whether the proposed move can get buy-in from key constituencies. This functions as a selection threshold. Hot market categories are more likely to be on an entrepreneur’s radar, to be seen as an attractive point of entry, and to be convincing to multiple people within a firm. They are perceived as more appealing to potential investors and more likely to lead to a favorable valuation. With all of this to recommend a proposed entry, specifics on why the organization will succeed in the market are not scrutinized as heavily. As one entrepreneur explains, “The best example is when we moved into the platform space. It wasn’t the perfect [fit] – it didn’t go head to head with the competition, [but] the potential was huge.” Another entrepreneur describes having to build capabilities from scratch to move into a market identified as high potential:

I interviewed forty [potential customers] and found that none of them cared about [what we were doing], that’s just not where the … market was … Arguably [we] didn’t have the capability to go in the direction we went. But we did it anyway and it was fine. We shifted toward a machine-learning based product. When we did that we didn’t have a single machine-learning based engineer. … We hired a math major out of college and told him to go learn it and he did … I think with Internet technology, it’s moving so fast that there isn’t deep expertise in it. So whether or not you think you’re capable … isn’t really an issue.

Entrepreneurs consider both the prospects of the market and how well they can compete in the market, when deciding to enter. Over-weighing market potential leads entrepreneurs to under-emphasize product-market fit. This means when perceptions of munificence are high, a wide range of entrepreneurs will enter, including those that are not ideally suited for the market. The consensus perception that a market is especially viable effectively lowers its barrier to entry.

On the flip side, firms in stigmatized markets are heavily scrutinized. An entrepreneur turned investor explains a non-consensus start-up’s difficulty attracting interest due to perceptions that it was in a bad market.
[Company A] … is in this Ad Tech market. And [Company B] is a public company that is worth [not a lot]. Because of [Company B] not being that valuable on the public market, [it] has made it almost impossible to get [a company in] Ad Tech funded. Because people are like, even if you execute with textbook perfect execution, [they are] the only comp on the public market … so there is just not a lot of upside for investors. I get their argument. So then what you have to do, you have to convince them this is different … this is a much hotter market. You have to educate people on that, but they mostly won’t buy it. If [Company B] was at $1 billion market cap? Boy, Ad Tech would be hot again. Because there’s this bandwagon effect.

Even if investors are open to resurrecting a once-stigmatized market category, entrepreneurs in those markets face scrutiny. A VC describes this with respect to the “online grocery” market that was rendered untouchable after Webvan’s failure in 2002:

[Investors require] more data. … What people will do is say, OK, Webvan didn’t work, tell me why you think it didn’t work and why you’re going to work. It’s a more robust conversation where someone needs to demonstrate a thoughtfulness around a particular topic.

Anticipating this response, entrepreneurs are unlikely to enter a stigmatized market if there is not a defensible product-market fit. Entrepreneurs who follow the consensus—entering markets that are widely seen as viable—face low levels of scrutiny as to how they will succeed. Non-consensus entrepreneurs face high scrutiny surrounding their ability to execute.

**Market Exit**

These arguments imply that consensus entry results in higher rates of market exit. Market entry depends on both the perceived viability of the market and how well the firm fits in the market. Positive events lead to a consensus that the market is especially viable. Focusing on this upside, executives overlook potential issues as to how well the firm can compete in the market, which translates into a lower selection threshold for market entry. As a result, consensus entrepreneurs, who enter after positive vital events, will be less viable (on average) in the market. Negative vital events lead to a lower perception of market viability. Entrepreneurs attempting to enter tainted markets will face tough questions from potential investors and may have difficulty
convincing internal parties to make the move. This scrutiny in terms of fit translates into a high selection threshold for entry. Only firms very well suited for the market will enter.\(^5\) So, the non-consensus entrepreneurs will be (on average) more viable in the market. In sum:

Hypothesis 2: Organizations that enter a market following positive (negative) vital events will be more (less) likely to exit that market over time.

Previous research in organizational ecology has linked founding conditions to subsequent survival rates using density—the number of organizations in a market—to measure founding conditions, varying over time within a population. Organizations founded in years with high density have higher mortality, which is attributed to competition weakening the firm (Carroll and Hannan, 1989; Swaminathan 1996). In contrast with studies that focus on density at founding, we take a step back and investigate what is leading to increased density in the first place. This is important because density can either indicate that a market is gaining traction or that the resource space is crowded (Carroll and Hannan, 2000). That high density can represent both good and bad market conditions might account for the varying effects of density at entry from previous studies. Here, we investigate a less ambiguous signal, positive and negative vital events.

**Entrepreneurial Success: VC Investment**

Our model also implies that consensus entry is hazardous to a firm’s financial prospects. One reason that firms follow the consensus path is because they are tracking where investors are

\(^5\) Any market entry requires multiple constituencies within the organization to agree on the course of action. In our terminology, consensus behavior refers to following the broader social consensus within an industry. Our argument suggests that consensus entry is frequent and non-consensus entry rare. But non-consensus entry does occur, and when this happens, the entrepreneurs who see the merits of a generally unpopular move have marshaled support from multiple parties within the organization.
putting their money. On the one hand, given that market viability is the primary focus of VC investors, consensus behavior might seem to be a sound strategy.

On the other hand, our model describes a dynamic where vital events trigger peaks and troughs of entries and entrepreneurs are least viable when entry is most common. This pattern is consistent with pejorative interpretations of “market herding.” VCs in software are wary of this trend and try to avoid taking part in collectively irrational fads. As one stated, “We don’t want to invest in ‘me-too’ ventures.” Multiple VCs articulated that they aimed to be “non-consensus and right.” This view is in tension with the dynamic described above, where VCs key off others’ investments to identify the most promising areas. VCs want to get into “hot” markets, but not by funding obviously “copycat” organizations. One VC described frustration with “me-too” ventures:

The pitch you get starts to sound really bizarre. I’ll give you an example … ‘we are building the Coursera meets Rap Genius for the gardener,’ … I don’t mind the analogy. But I want to understand what is the similarity. What is the market insight that Coursera or Rap Genius had that is really working … why does that translate well for you?”

VCs invest in hot markets, but they choose the most viable firms in that market—not the ones that followed the consensus, who are likely to have poor market fit. Consequently:

Hypothesis 3: Entering markets following positive vital events will reduce an organization’s hazard of receiving venture capital funding.

As with the often-quoted Yogi Berra aphorism, “Nobody goes there anymore. It’s too crowded,” VCs flock into hot markets but try to avoid funding businesses that do so. Observing that VCs invest following positive events, entrepreneurs might believe that entering these markets will
increase their chances of securing funding. But this belief ignores an important caveat: even though VCs invest in hot markets, they avoid the “me too” firms in those markets.

*Entrepreneurial Success: IPO*

Finally, we apply our model to a firm’s chances of going public, an important measure of entrepreneurial success. In the wake of positive events, VC investment floods into “hot” markets (hypothesis 1b). This means VCs will have to compete to fund the best firm. Those eager to get into the market will have to choose a less viable organization. By contrast, in markets with a dearth of VC attention, an investor will be able to secure the top organization in its market category. This implies that the average viability of funded firms will also decline in the wake of positive events. In addition, exaggerated assessments of a market’s potential will lead to an oversupply of funded organizations, where there are more well-financed competitors than is warranted for future demand. As one VC described:

[There are investors who] say, we just really like this space, and I’m not sure they’ve really thought about the space. I think there [are] three on-demand valet services in San Francisco that are venture funded. They’ll come and pick up your car and park it some place for you. And, it’s just unreal. There are three of them, they’re venture funded.

These arguments imply that organizations funded during a flood of investment in their market are less likely to achieve long-term success. Given that long-term success in the software industry typically means transitioning to public ownership through an IPO, this implies:

Hypothesis 4: Organizations that receive venture capital funding during a flood (drought) of investments are less (more) likely to later go public.

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6 In the software industry, market categories are referred to as “market spaces.”
Empirical Context: The Software Industry

We study these ideas in the context of the software industry between 1990 and 2002. The software industry is fast-paced and innovative, with producers and investors vying to identify the next hot market. Market categories are important in this domain. They help people evaluate complex products that are difficult to understand (Wang, 2009; Pollock and Williams, 2009; Pollock and Williams, 2011). Market categories are typically based on function or product use. They emerge when the community comes to agreement that a category identifies a type of product. Some examples are: “business intelligence,” “customer relationship management,” “systems software,” “middleware,” “enterprise resource planning,” and “digital audio.” Market category definitions are not owned by any one group: they are maintained through interactions among multiple audiences—entrepreneurs, established organizations, analysts, investors, and customers. For entrepreneurs, market categories are especially important. In their in-depth study of five entrepreneurs, Santos and Eisenhardt (2009) conclude that setting market boundaries is crucial to entrepreneurial success. Market definition is a core part of entrepreneurial strategy.

Market categories provide a frame for what an organization does: what its products can be used for, its potential customer base, and who its competitors are. Organizations identify with market categories to try to attract and retain the right types of customers. For entrepreneurs, they also indicate the company’s potential to interested investors. But as is the case in many domains, software categories are subject to trends (Wang, 2010). The faddish nature of this domain led Gartner, the leading IT analyst, to create a “hype cycle” report that charts a market through what they define as a cycle that includes “inflated expectations” and a “trough of disillusionment.” To stay current, market actors must keep track of which categories are hot and which have become passé.
VC is important in the software industry. VCs invest in early stage organizations, betting on a firm becoming a large financial success. Such investments have been credited with the outstanding growth of the software industry (Onorato, 1997). Attracting VC is critical at early stages—often more important than attracting customers. In their investment decisions, VCs look for a strong management team, a good business plan, and a growing market (Tyebjee and Bruno, 1984; MacMillan, Siegel, and Narasimha, 1985; Gompers and Lerner, 2001). Kaplan et al. (2009) argue that it is a better investment strategy to weigh the business idea more heavily than qualities of the management team.

VCs fund companies that have the potential to revolutionize the industry and generate outsized financial returns (Hirsch, 1972; MacMillan, Siegel, and Narasimha, 1985; Pontikes, 2012) – the next “new, new thing” (Lewis, 2000). Microsoft, Oracle, Google, and Facebook are examples of exceptional successes that enticed entrepreneurs and financiers alike. But the industry has also been a site for spectacular failures. Prominent bankruptcies such as those by System Software Associates, BuildNet, or Lernout & Hauspie are cautionary tales. The success of a company depends heavily on whether it can dominate a market. As one VC conveyed, the “ultimate size of [the] market addressed is the single most important determinant of outcome.” Uncertainty surrounding markets, the large upside potential, and the importance of market category reputations makes this a good context to study long-term effects of consensus and non-consensus market entry.
Data

To test the hypotheses in this paper, we assembled data on software organizations, the market categories they are in, when they receive VC funding, and when they IPO. Our final data contain 4,566 organizations in 456 different market categories over 13 years.

Our initial source of data was the 269,963 press releases issued between 1990 and 2002 that had at least three mentions of the word “software,”7 gathered from PR Newswire, Business Wire, and ComputerWire. We used a combination of automated text analysis programs and hand coding to extract every software organization that could be identified in these texts, resulting in 4,566 firms.8 Press releases are an important medium for software companies to convey news and create a public profile. They are frequently used in media reports (Soltes, 2009). Most software organizations issue press releases, including small, young companies that are missing from standard data sets.

In almost every press release, software organizations identify the market categories they are in, typically in an “about” section at the end of the press release. For example, in a 1999 press release, Accrue writes, “Accrue Software, a leading provider of e-business analysis software and services…. ” We extracted every identity statement for every software organization in our data. This provides a record of market categories each firm was in every year.

Software companies identify with market categories at the firm level, not at the product level. Many firms do not even mention specific products in their press releases. This is also the case for software analysts and industry media. Gartner ranks organizations, not products, in their

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7 Press releases are available in electronic format starting in 1985. We found that coverage of software companies becomes comprehensive by 1990. We use press releases from 1989 to construct lagged variables.
8 To extract software organizations, we compiled a list of words and phrases preceding Inc, Corp, Co, LLP, or a capitalized Software. This cast a wide net of firms and junk phrases. After automated cleaning, the list was sorted through by hand to determine which were software companies.
Magic Quadrant reports. *Software Magazine*’s Software 500 assigns market sectors at the company level. In this industry, firms, not products, are usually the main unit of categorization.

We identify the market categories each firm is in for each year using the identity statements. We compiled a list of market categories covered in articles from industry publications *Software Magazine* and *Computerworld*. We then read through the statements for additional categories. Therefore, our data capture early-stage market categories organizations use that do not catch on in the media. We then searched identity statements for categories on the list. Our final data contain each category each firm is in every year: 4,566 software organizations and 456 market categories between 1990 and 2002.

Press releases contain self-reported market category affiliations. Previous research indicates that self-claimed categories are relevant. For example, self-reported markets (from 10K statements) have been found to be a better predictor of financial outcomes as compared to SIC or NAICS codes (Hoberg and Phillips, 2010; Hoberg and Phillips, 2012). Research using press releases finds self-reported markets to be predictive of receiving venture capital financing (Pontikes, 2012) and media coverage (Kennedy, 2008). They also reflect an organization’s technical capabilities (Pontikes and Hannan, 2014).

We ran a number of tests to check the validity of these data. First we investigated whether categorization in press releases reflected the firm’s public presentation, for a sample of organizations. We found that market affiliations in press releases were consistent with claims on their Web sites (using the archived Web) and in their annual reports (for public firms). Gartner covered over half of the market categories, indicating that market categories in our data reflect shared industry classification.
These data contain all software organizations. To study entrepreneurs, we only include firms in their start-up phase. We define this based on firm age and whether the firm has undergone an IPO. To focus on entrepreneurs, we analyze companies in their pre-IPO phase. We gather IPO information for each software organization using data from Thomson Financial and data maintained by Jay Ritter.\(^9\) We exclude all public organizations from our analysis.

We also wish to exclude old, private organizations no longer in their entrepreneurial phase. To do this we profile entrepreneurial firms based on age. The mean age to IPO in this time period is 8.5 years with a standard deviation of 3 years.\(^10\) We exclude firms older than one standard deviation above the mean, or more than 12 years old (for the market entry and exit analyses), to omit those no longer in the typical entrepreneurial phase.\(^11\) To compute firm age, we searched for founding dates in the press releases and from Hoovers, BusinessWeek’s private company information, the company’s Web site, or Wikipedia. Founding dates were located for 3,705 of the 4,566 organizations. Firms where founding dates cannot be traced are likely to be the firms that were not able to attract funding and faded away with little trace (except through press releases). Excluding these firms would bias our analyses. Therefore, for the market entry and exit analysis, we include all private firms that are 12 years and younger, or those for which founding dates could not be located: 3,387 firms.

To measure positive vital events, we use data on when firms receive venture capital financing, which come from the Venture Economics database maintained by Thomson Financial. We only include venture capital deals. We searched for VC funding for every software organization in the press release data. 822 private organizations receive venture capital funding in one or more years.

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\(^9\) [http://bear.warrington.ufl.edu/ritter/ipodata.htm](http://bear.warrington.ufl.edu/ritter/ipodata.htm)

\(^10\) [http://bear.warrington.ufl.edu/ritter/IPOStatistics.pdf](http://bear.warrington.ufl.edu/ritter/IPOStatistics.pdf)

\(^11\) Firms that are acquired drop out of the data.
For negative vital events, we use bankruptcies gathered from Thomson Financial, and augment this with organizations that are coded as “defunct” by Venture Economics.\textsuperscript{12} Bankruptcies are relatively rare—only 68 in these data. It is common knowledge in the industry that failures often take place as a market exit without bankruptcy. Therefore, we investigate the effects of market exits as well as bankruptcy in our hypothesis tests.

We augment these data to construct control variables. We use the historical record of firms ranked in Software Magazine’s Software 500, which ranks the top 500 public and private software firms by revenue, to control for size. We identify firms that patent using data from the U.S. patent office, maintained by the National Bureau of Economic Research (NBER) (Hall et al., 2001).\textsuperscript{13} We also track the number of acquisitions made by the firm by searching press releases for acquisition announcements.

The result is a longitudinal data set of characteristics of software organizations and market categories, updated yearly between 1990 and 2002. Software classification changes over time. Our data allow us to construct time-varying variables to capture these dynamics.

**Empirical Models**

*Market Entry and Exit*

To test hypothesis 1a, predicting entrepreneurial entry into market categories, we construct a data set of organization-market dyads, for all entrepreneurial organizations paired with market categories that they are not in (the “target” market). A dyadic analysis allows us to control for both organization and market characteristics. A dyad enters the risk set the first year both the organization and target market category are observed in press releases. When an

\textsuperscript{12} In the interest of parsimony, hereafter we refer to all negative events as bankruptcies.

\textsuperscript{13} NBER patent data are available through 2006.
organization enters the target market, an event occurs, and the dyad is removed from the risk set. We only include a firm’s entrepreneurial phase in this analysis: when an organization turns 13 or has an IPO, it drops out of the risk set and is a censored observation. These data contain 1,335,633 potential organization-market dyads over 3,505,317 organization-market-years, with 6,537 market entries.

We estimate the hazard of market entry:

\[ r_{e:Ak}(t) = r_{e:Ak}(t)^* \times \exp[\alpha F_k + \beta V_k], \]

where \( r_{e:Ak}(t) \) is the instantaneous rate of entry of organization \( A \) into market \( k \), varying as a function of duration \( t \) since the organization \( A \) was first at risk of entering market \( k \), and \( r_{e:Ak}(t)^* \) is a baseline rate specified as a function of controls. \( r_{e:Ak}(t) \) is a function of the independent variables: \( F_k \) counts the number of bankruptcies in market \( k \) in the prior year, and \( V_k \) is the number of venture capital funding events in market \( k \) in the prior year. By hypothesis 1a, we expect to find \( \alpha < 0 \) and \( \beta > 0 \).

In calculating \( F_k \) and \( V_k \), we account for the fact that some organizations are in multiple market categories. We weight each bankruptcy or funding event by the organization’s grade of membership in the market. This is calculated as the number of times organization \( A \) claims market category \( k \) in press releases, divided by the number of times it claims any other market. Throughout all our models, measures of \( F_k \) and \( V_k \) are calculated using grade-of-membership weights.

Hypothesis 2 looks at the exit of organizations from a market category depending on whether the organization entered in the wake of vital events. We create a risk set, for each year,

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14 For organizations that move into and out of categories, only the first entry is counted as an event. We do not count the market category that the organization is in when it appears in the data as an entry event because the dyad has just entered the risk set, and so cannot be estimated with hazard rate models. We ran additional analyses of negative binomial estimations on the first observed market entry; results are consistent.
including dyads of all entrepreneurial firms and the market categories they are in. An exit is defined as the last consecutive year the organization is in the market category since entry.\textsuperscript{15} We study market exit only, and organizations that exit the data altogether are a censored observation. Exits are undefined for the year 2002; the exit analysis is run for years 1990 through 2001. There are 12,026 organization-market dyads across 19,437 organization-market-years and 6,738 market exits.

The category exit rate is modeled according to:
\[
n_{h;Ak}(\tau) = n_{h;Ak}(\tau)^* \times \exp\{\gamma_\tau F_{k,\tau=1} + \delta_\tau V_{k,\tau=1}\},
\]
where \(n_{h;Ak}\) is the exit rate of organization \(A\) from market \(k\), varying over \(\tau\), the duration that organization \(A\) has been in market \(k\). \(n_{h;Ak}(\tau)^*\) is the baseline rate specified using control variables. \(F_{k,\tau=1}\) and \(V_{k,\tau=1}\) measure, respectively, the (weighted) number of bankruptcies and venture capital investments in market \(k\) at the time of organization \(A\)’s entry into the category (\(\tau=1\)). We allow estimates of the effects of \(F_{k,\tau=1}\) and \(V_{k,\tau=1}\) to vary over time \(\tau\), to test our argument that the enduring effects of entry conditions take time to materialize. According to Hypothesis 2, we expect to find \(\gamma_\tau < 0\) and \(\delta_\tau > 0\).

In both the entry and exit models, we include a number of controls. Market covariates include the number of organizations in the market category, entries into, and exits from the market. These are weighted by grade of membership and logged as they exhibit skew. We include the leniency of the market category to control for boundary porousness (Pontikes and Barnett, 2015).\textsuperscript{16} We also include the age of the market (measured since the inception of our data). Organizational covariates include the number of markets the organization is in (logged),

\textsuperscript{15} Some organizations move into and out of categories. Because we are interested in effects of entry conditions, we define exit as the first observed exit, and thereafter the dyad is removed from the risk set.

\textsuperscript{16} This is computed using contrast, or the average grade of membership of organizations in the market. \(\text{Leniency} = (1 - \text{contrast}) \times \ln(N_{ocat}),\) where \(N_{ocat}\) is the number of overlapping categories.
whether the organization appeared in Software Magazine’s Software 500 rankings to measure size (small or large), whether the organization received venture capital funding in the previous year, the time since the organization last entered/exited any market, and the organization’s tenure in the data.\textsuperscript{17} Year dummies are included in all models.

There is a concern in dyadic models that there is interdependence between observations because actors appear in multiple dyads. We address this in two ways. For firm autocorrelation, we include an autoregression control advocated by Lincoln (1984), defined as the mean of the dependent variable for all observations including firm $A$, excluding the $A$, $k$ dyad, in the given year. To test against market autocorrelation, we run models that include dummy variables for each market category (Mizruchi, 1989).

We specify duration using a piecewise exponential model. We obtain estimates using the software package STATA. Spells are split by: 0-1 year, 1-2 years, 2-4 years, and 4+ years. Standard errors are clustered by category.\textsuperscript{18} In all models, independent variables are lagged by one year.

\textit{VC Funding and IPO}

To test hypotheses 1b, 3, and 4, models are estimated for the VC funding rate and the IPO rate, with the organization as the unit of analysis. The risk set is privately held companies including the years a company was private before it went public. We restrict the risk set by age to exclude old, private organizations that are neither seeking funding nor are interested in going public. For the VC analysis, we include organizations less than 15 years old, and for the IPO analysis we include those 20 years and younger (or where the founding date is not known). Age

\textsuperscript{17} The time since last category entry/exit is measured for the organization, and is not equivalent to the hazard clock, which is measured for the dyad.

\textsuperscript{18} In models where category dummies are included, standard errors are clustered by firm.
thresholds are chosen based on when the data show a substantial drop-off in number of VC funding events or IPOs. The risk set for the VC financing estimation includes 3,551 organizations across 10,538 organization-years, experiencing 1,527 VC funding events. For the IPO analysis, we also exclude firms that enter the press release data the year they go public, since we do not have histories of these firms. The risk set for the IPO estimation includes 3,633 organizations over 11,805 organization-years with 356 IPO events. Note that the funding histories of these firms are limited to events that occurred after any press release was issued.

The model of the instantaneous rate of VC funding is:

\[ r_{vj}(\theta) = r^*_vj(\theta) \times \exp[\epsilon V_j + \zeta C_j], \]

where \( r_{vj}(\theta) \) is the rate of VC funding of organization \( j \), varying as a function of duration since last funding \( (\theta) \), and \( r^*_vj(\theta) \) is a baseline rate specified as a function of control variables. \( V_j \) tests hypothesis 1b. It is computed as the average number of (prior year) venture capital fundings across all categories \( k \) that organization \( j \) is in, for the given year, weighted by \( j \)’s grade of membership in each category \( k \). We expect to find \( \epsilon > 0 \), that an organization’s chance of receiving VC funding is increased by being in a category that has recently received funding. We estimate models that include \( V_k \) using a quadratic and a piecewise specification, to allow for nonlinearities in the functional form of this effect.

We test hypothesis 3 using \( C_j \), which measures whether organization \( j \) follows VC funding in its market entry. We construct \( C_j \) as the number of markets organization \( j \) entered for which weighted VC funding events is greater than or equal to 2 in the previous two-year moving window. We take the natural log to reduce skew. Hypothesis 3 predicts that \( \zeta < 0 \).

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19 Results are not sensitive to the age threshold.
20 We also estimated models using different thresholds for VC funding events, as well as a one-year window.
We also include controls: the fuzziness of the organization’s categories (1- contrast), which has been shown to affect evaluations (Kovács and Hannan, 2010; Negro, Hannan, and Rao, 2010; Pontikes, 2012).  

We include the number of organizations in the focal organization’s categories (weighted by grade of membership), to control for market competition. We include the organization’s tenure (since inception in the data), its number of patents, number of acquisitions, and whether the organization was included in Software Magazine’s annual ranking of the top 500 software firms account for differences in size, resources, and quality. We also control for the number of rounds of financing the organization has received.

The transition from private to public ownership is modeled as:

$$ r_{pj}(\alpha) = r_{pj}(\alpha)^* \times \exp[wV_{kf}] $$

where $r_{pj}(\alpha)$ is the IPO rate for organization $j$, varying as a function of its tenure in the press release data $\alpha$, and $r_{pj}(\alpha)^*$ is the baseline rate as a function of controls. $V_{kf}$ measures the number of VC investments in category $k$ in the year that firm $j$ was funded. Hypothesis 4 predicts that $w < 0$.

We calculate $V_{kf}$ in two ways. The first measure computes $V_{kf}$ as $V_k$ in the year the organization receives its first round of funding. The second measure computes $V_{kf}$ as the mean of $V_k$ over all years $j$ receives funding, updated for each year.

Controls for the IPO models include: the number of organizations in the focal organization’s categories (weighted by grade of membership), to control for market competition, and the number of categories the organization is in, to account for generalism. We control for

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21 We use fuzziness instead of leniency because it is more predictive in funding models. Results in all models are robust to including leniency.

22 In models of funded firms only, the clock begins at first funding.

23 The number of fundings is weighted by the funded organization’s grade of membership in the market category. For organizations in multiple categories, we average over its categories, weighted by the organization’s grade of membership.
whether the organization previously received venture capital funding, number of funding rounds, whether it has patented, and if ranked in the Software 500 in the previous year, to control for size and quality.²⁴

We specify duration to funding and IPO using a piecewise exponential model in STATA. In VC models, spells were split by: 0-1 year, 1-3 years, 3-5 years, and 5+ years. VC funding is a repeat event; when a firm is funded, it re-enters the risk set as a new observation. Therefore, we cluster standard errors by firm. For IPO models, spells were split by: 0-1 year, 1-3 years, 3-5 years, 5-7 years, and 7+ years. Different piece lengths were used to accommodate expected time trends for the different dependent variables. Results are not sensitive to the length of pieces. All independent and control variables are lagged by one year.

Results

Market Entry

Table 1 provides descriptive statistics for the entry analysis. Correlations are included in the appendix. Table 2 reports the market entry estimates, including effects for independent variables and select controls. Column 1 is a baseline for comparison. Column 2 includes a category’s venture capital fundings in the previous year, to test hypothesis 1a. The effect is positive and significant at p < 0.001. Column 3 continues the test of hypothesis 1a by including the number of prior bankruptcies in a category. This term has a positive effect on entry, marginally significant at p < 0.10. Results provide support for hypothesis 1a in terms of positive vital events: organizations enter markets following VC investment.

--- Insert tables 1 and 2 about here ---

²⁴ Different controls are included in the VC and IPO models based on theoretical relevance and if they had a significant effect at the p < 0.05 threshold. Significant controls were not excluded, and reported effects are similar when all controls are included.
Column 4 in table 2 includes the VC funding variable in pieces, to test the functional form of the effect. The variable has a monotonic positive effect: the more organizations in a market that receive funding, the higher the subsequent rate of entry. Column 5 includes category fixed effects. The effect of VC funding on entry remains positive and significant at p < 0.001, indicating that it is not heterogeneity among categories that is driving the result. The bankruptcy effect is not significant when category fixed effects are included (column 5). We do not find support for our hypothesis in terms of bankruptcies. But there is a negative effect of lagged exits from a category on the ensuing entry rate. This evidence is consistent with a pattern where new entrants are deterred from moving into markets that are seen as less attractive due to prior failures.

All models control for the size of the market (number of members) and its momentum (entries and exits), which are indicators of the amount of legitimacy and competition within a market (Hannan and Freeman, 1977). Effects suggest that in this context, the promise of getting into a high-potential market outweighs competitive concerns: the larger the market and the more entries, the higher the entry rate; the more exits, the lower the rate.\textsuperscript{25}

Table 3 presents models that explore these effects and test against alternative hypotheses. Our theory proposes that positive vital events lower the threshold for market entry. We expect entries to occur right after the threshold is lowered. To test this, column 1 reports an estimate that includes VC fundings in the market two years prior. This does not have a significant effect on entry, while the effect of prior year VC funding events remains. We further explore the effect of

\textsuperscript{25} We also ran models allowing for a non-monotonic density effect (fuzzy density and fuzzy density squared), and neither term has a significant effect. The positive effect of number of venture capital funding events remains.
recent vital events by running a model that uses six-month spells (column 2).\textsuperscript{26} Results show that it is positive vital events in the most recent period that have a positive effect on entry.\textsuperscript{27}

--- Insert table 3 about here ---

Column 3 in table 3 includes controls that test against a number of alternatives. We investigate whether VC investment is capturing other types of market prominence by controlling for the number of organizations in the market category that are ranked in the Software 500, to capture markets where there is strong demand. We cannot reject the null that it has no effect on entry. It does not change the effects reported above.

Another concern might be whether these effects are due to technically advanced markets drawing entry and also receiving funding. To test this alternative, we include the number of patenting organizations in the market. This variable has a positive effect on entry, but the effect of VC fundings remains. We also expect an organization’s technical similarity to a market category to increase its likelihood to enter (Pontikes and Hannan, 2014). Such proximity could account for our effects if markets that are technically closer to organizations are also more likely to be funded. We test against this by including a variable that measures an organization’s technical proximity to a market category based on citation overlap between its patents and patents issued to members of the market (see Pontikes and Hannan (2014) for details of this measure). The positive effect of venture capital fundings on entry persists with the inclusion of these controls.

Our argument about vital events changing social perceptions implies that there might be differences based on the prominence of the VC firm making the investment. To investigate this,

\textsuperscript{26} For some press releases (1.5%), we extracted the year but not the date of the release. We randomly assigned these to a six-month period within the year of release. The random assignment does not affect reported results.

\textsuperscript{27} This should not be interpreted as funding two periods prior being irrelevant to entry, as there is a high correlation between VC fundings in adjacent periods (0.71).
we conduct an exploratory analysis. Column 4 in table 3 presents estimates that separate vital events based on the status of the VC investment firm. We measure status using the LPJ reputation index, which provides yearly VC reputation scores based on funds under management, number of start-ups invested in and amount invested, number of companies taken public, and the firm’s age (Lee, Pollock, and Jin, 2011). We separate the VC funding variable into pieces based on whether the VC firms investing in the market were low-status firms according to this index.28 We find that consensus entry follows investment of high- or middle-status VCs; the effect for low-status firms is not statistically significant due to a decrease in the coefficient (the coefficients are different at $p < 0.12$). This suggests prominent vital events drive consensus behavior.

**VC Funding Analysis**

Table 4 includes descriptive statistics for organization-level data used in the venture capital funding analysis (correlations are in the appendix). Table 5 reports results. Column 1 is a baseline for comparison. Columns 2 and 3 test hypothesis 1b. The estimation in column 2 shows that there is a quadratic effect of the number of venture capital fundings in an organization’s market category (in the previous year) on the rate of an organization receiving VC funding. VCs are influenced by vital events, but the influence reaches a saturation level. We include piecewise levels of venture capital fundings in column 3. Results show a clear non-monotonic effect:

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28 We code investments as low-status if all VC firms that invested were ranked 150 or above in the LPJ index. The LPJ index ranks around 1,000 firms per year. 150 is a relatively high threshold that likely includes what insiders would consider both high- and middle-status firms. We do not find differences if we use a finer distinction between high and middle status. Some investment firms in our data are not included in the LPJ index. We find that investment by excluded firms has a similar effect to those ranked above 150. As a result we pool these in the “all other VC” variable.
positive and increasing up until 15 fundings, thereafter falling to become negative and non-significant. This provides support for hypothesis 1b for most of the observed range of funding.

--- Insert tables 4 and 5 about here ---

Columns 4-5 contain estimates that test hypothesis 3, that organizations that “chase” VC funding by entering hot markets are less likely to receive investment. Column 4 includes the number of categories an organization enters following two or more VC funding events in the previous two-year window. The effect is negative and significant, and substantial. Having entered just one category following two or more VC funding events in the previous two years cuts in half the net benefit the organization receives from being in a hyped category. Entering two categories following two or more fundings erases any benefit the organization receives from being in a hot category. This pattern is illustrated in figure 1.

--- Insert figure 1 about here ---

Results are similar if we use a one-year window, with weaker significance (p < 0.15), or if we do not take the natural log (p < 0.05). However, if we reduce the threshold to include category entry following any VC fundings, the result loses significance due to a decrease in the coefficient. This pattern is consistent with the results from the entry and funding models, which show a jump in market entry following two or more VC fundings.

We test whether this effect is a result of organizations that engage in market search. Column 5 includes a control for the number of categories the organization entered and exited in the previous year. This variable does not have a significant effect on receiving funding, and results reported persist with the inclusion of this control.

The effects of controls are noteworthy. The number of prior rounds has a positive effect. Conditional on the number of rounds of funding received, organizations with higher tenure are
less likely to be funded, likely picking up on heterogeneity among firms. The fuzziness of an organization’s categories has a positive effect, consistent with previous research that shows venture capitalists have a preference for ambiguity (Pontikes, 2012). There is a trend that VCs are more likely to fund an organization in larger categories. Results persist when additional controls are included: the number of markets the organization is in, the number of Software 500 organizations in the organization’s market, and the number of patenters in its markets.

**Market Exit Analysis**

Table 6 reports descriptive statistics for the market exit analysis (correlations are available upon request). Table 7 reports estimates of piecewise continuous hazard rate models on the likelihood an organization exits a market category, to test hypothesis 2. Bankruptcies and venture capital funding events at the time of the organization’s entry into the market are included in time pieces to test how they affect exit from the market over time. In columns 1 and 2, vital events are measured the year before entry, both without (column 1) and with (column 2) category fixed effects. In column 3, we measure VC fundings in the market category six months prior to entry, revisiting the exploratory analysis of recent vital effects on entry (column 2 of table 3). Results show a pattern that supports hypothesis 2. Firms that enter a market category after bankruptcies are especially likely to survive in that market, whereas those that enter after many VC fundings are increasingly likely to leave.

--- Insert table 7 about here ---

There are different thresholds after which these effects manifest: after two years for bankruptcies, and after four years for VC fundings. In columns 4-6, we collapse time pieces in line with these empirically derived thresholds to reduce noise, resulting in stronger significance.
The model in column 4 shows that organizations that enter categories after bankruptcies are less likely to exit after two years in the category, significant at p < 0.05. Those that enter after VC fundings are more likely to exit after four years, significant at p < 0.08. Results are consistent in column 6, which uses entry after VC fundings in the previous six months (p < 0.05). Effects are also similar when category fixed effects are included in column 5 (p < 0.10), suggesting that differences between categories does not account for the effect. These results support hypothesis 2. Non-consensus entrants, who follow negative vital events, are more viable in the market over time. But consensus entrants, who follow positive vital events, are more likely to exit. These effects are illustrated in figure 2.

--- Insert figure 2 about here ---

All models control for current-time competition, recent entries, and exits. The number of firms in the market category has a negative effect on exit in models without category dummies, and a positive effect when category fixed effects are included. This result indicates that markets with more potential draw more firms, but for a given category, crowding leads to higher competition and exit. The number of entries has a negative effect and number of exits a positive effect: firms are more likely to stay in market categories that are gaining momentum. Results are similar with the inclusion of additional controls: recent venture capital funding events and bankruptcies, the number of Software 500-ranked organizations and the number of patenting organizations in the market, the firm’s technical proximity to the target market and to other markets, and the number of patents issued to the organization (models available upon request).

IPO analysis
Table 8 provides descriptive statistics for the IPO analysis (correlations available upon request). Table 9 includes model estimates. Column 1 serves as a baseline and columns 2-6 test hypothesis 4. Column 2 reports an estimate that includes the average VC fundings in the organization’s markets across all years it received funding. This effect is non-significant. Columns 3 and 5 report VC fundings in the organization’s market when it received its first round of funding, using the non-transformed count (3), and the natural log of the count (5). The effect is negative and marginally significant (p < 0.10) for the non-transformed measure, and non-significant when the logged measure is used. Columns 4 and 6 restrict the risk set to funded organizations. Results show a positive and significant effect (p < 0.05) for both measures. These results provide qualified support for hypothesis 4. Consensus VC investment is detrimental at the initial round of funding, but there is no detectable effect for later stage investment in hot market categories.

--- Insert tables 8 - 9 about here ---

Effects of controls show that larger organizations, those previously funded, and those with at least one patent are more likely to go public. Organizations are less likely to go public if they are in crowded categories. Organizations that are in many different categories are considerably more likely to go public, suggesting a premium on scope at least within the software industry. We also estimated models that included the venture capital fundings in the market in the previous year, fuzziness of the organization’s markets, its number of patents, the number of Software 500 organizations and number of patenting organizations in the market; these variables do not have a significant effect on an organization’s IPO rate, and results are similar to those reported above.

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29 Funded organizations are those that receive funding after appearing in the press release data.
Additional analyses

Entrepreneurship in established firms

Our study focuses on the entrepreneur. In recent years, there has been a push toward recognizing entrepreneurship in established companies, especially in high-technology. In *The Lean Startup*, Eric Ries comments that entrepreneurs include “general managers, mostly working in very large companies who are tasked with creating new ventures or product innovations … they are visionaries … prepared to take bold risks to seek out new and innovative solutions…” (p. 25). In our interviews, investors and entrepreneurs described established companies like Google and Facebook as entrepreneurial. So it is informative to compare market entry for young entrepreneurs to established companies. We ran entry and exit models on public companies, and results are similar. Like entrepreneurs, public companies enter market categories following VC funding events. And those that enter following bankruptcies are more likely to stay, while those that entered following VC funding are more likely to exit (models available upon request). As public firms are not looking for VC investment, these effects highlight that VC fundings are an indicator of the overall promise of the market. Established firms engage in similar processes of entrepreneurial search and realize the same long-term consequences for consensus and non-consensus behavior.

Density at entry

As described above, previous work suggests that intense competition at founding can lead to long-term hazards, generally attributed to resource scarcity (Carroll and Hannan, 1989; Swaminathan, 1996; cf. Barnett et al., 2003). We propose that high density at entry can indicate either fierce competition or market promise, as borne out in our data: the correlation between
venture capital fundings and market category density is high—around 0.8. We think VC funding events are a clearer indicator of perceived market potential. Even so, we explored this question in additional analyses, including variables that measure entry into high-density market categories for the exit, VC funding, and IPO analyses. In all three cases, the high correlations between these variables add noise to the model and neither variable is significant at conventional levels (models available upon request). Empirically, it is difficult to tease apart effects of density at entry from effects of VC funding. But given that VC funding is a sign of market potential and increasing demand, the high correlation suggests that researchers should not assume that high density at entry is simply an indicator of a difficult competitive space. One should also consider other factors that indicate the market is promising, such as vital events, which lead to high density.

Discussion

Evolutionary approaches to studies of entrepreneurship show that consensus behavior is common. Most research seeks to understand factors that underlie these herding processes. Less studied are the subsequent effects of market entry choices. We develop a model that predicts long-term consequences to market herding. We model market entry as a selection process and propose that vital events change the selection threshold. This is because vital events lead to exaggerated perceptions of a market’s potential. After positive vital events, there is a consensus that a market category is an especially attractive place to compete, and after negative vital events there is the opposite assessment. We argue that these assessments change the level of scrutiny for organizations entering a market in terms of how suited the company is to compete in the area. Consequently, these processes shape the average viability of firms that enter a market following positive and negative vital events.
The estimates of our models are in line with our predictions. First, we find evidence consistent with herding behavior in response to consensus views. Positive vital events trigger a flood of market entries and venture capital investment. Next, we find harmful effects for organizations and VCs that follow the consensus in terms of market viability, receiving investment, and the likelihood of going public.

Although non-consensus behavior may seem like foolishness at the time, it turns out to be a wise alternative – if the organization can weather the heightened scrutiny. Consensus entrepreneurs can readily garner support to enter a hot market, but as a result are less viable (on average). This leads to rapid exit, and as a result consensus entrepreneurs suffer from instability in their long-term market identities. They move into and out of markets as hype cycles evolve. Organizations that enter hot markets in the hopes of gaining some of the benefits bestowed on their competitors find themselves late to the party, in an over-crowded market where resources have become sparse. They are ill suited to their markets and thus are less likely to receive VC funding—even accounting for the fact that venture capitalists also rush into hyped markets. They are then more likely subsequently to exit, perhaps looking for the next new fad, and the process starts anew. Where non-consensus organizations build a stable identity over time, consensus firms rapidly change their affiliations, incurring risks associated with major organizational change (Barnett and Carroll, 1995). Tracking on markets that are “blessed” by positive vital events establishes an organization as a perpetual follower.

Non-consensus entrepreneurs, who resist entering faddish markets and may even enter those that are tainted, realize better long-term outcomes. They face high levels of scrutiny about how they will be able to succeed, both from people within the firm and outside parties, which functions as a high entry selection threshold. This strengthens the firm’s product-market fit. Non-
consensus entrepreneurs therefore are more likely to thrive in the long run. Industry participants have intuitions about this pattern. One VC we interviewed stated:

[Entrepreneurs] absolutely [key off hot markets] and that’s a problem. … The only way to achieve success as an entrepreneur or as an entrepreneurial investor is to be non-consensus and right. Because if you’re consensus and right, then everyone’s doing it and all the returns go away. If you’re wrong, it doesn’t matter if you’re consensus or non-consensus, you don’t succeed. The problem … is that the bulk of the capital and talent flows to consensus right.

Many investors and entrepreneurs in our interviews concurred they aimed to be “non-consensus and right.” The difficult part about taking the non-consensus path is that it is only clear after the fact if the entrepreneur is also “right.”

Our findings show that conformity at the investor level also does not pay, but only for first round funding. This is in line with the idea that an investor (or entrepreneur) should be “non-consensus and right.” Ideally, VCs will invest in a market category before it becomes hot. This is underscored by our IPO findings: there is a negative effect for organizations that received their first round of funding in a market category following positive events, but no effects across all funding rounds. Investors that follow others in their first investment exhibit consensus behavior. But those that provide subsequent funding rounds likely invested in the category before the hype. Many of these were initially non-consensus investors that turned out to be “right.”

It is important to keep in mind that the value of non-consensus behavior comes from entrepreneurs and investors applying additional scrutiny to how well-suited their organization is to a particular market. The problem with following the consensus is that firms over-prioritize market viability, leading them to under-emphasize product-market fit. Knee-jerk non-consensus behavior – for example seeking out tainted markets regardless of product-market fit – would likely also result in adverse consequences. As prominent VC Peter Thiel writes in Zero to One, “you can’t escape the madness of the crowds by dogmatically rejecting then … The most contrarian thing of all is not to oppose the crowd but to think for yourself.” (p. 22) It is important
for entrepreneurs to scrutinize any move and carefully consider how their firm can uniquely compete in a space. Our study indicates that market potential looms large for entrepreneurs and investors, leading many to take shortcuts in estimating how well they can compete in a hot market. Rather than simply lamenting rampant consensus behavior, it may be wise for industry participants to focus less on which market is hot, and turn attention toward the more nuanced—and perhaps more difficult—task of analyzing a firm’s product-market fit. Such a shift would encourage the non-consensus behavior both investors and entrepreneurs say they support.

The role of vital events implies that the popularity of markets may change abruptly. If vital events were simply indicators of the quality of a market—which presumably does not change rapidly—then one might expect the evolution of markets to converge slowly on a steady-state level of organizational activity. But vital events trigger a discrete change in appraisals. As a result, markets that may have once seemed attractive may rapidly be tainted by negative events such as bankruptcies, and unattractive markets will be seen as lucrative once a salient success takes hold. Our findings are in line with this pattern of rapid updating. Entrepreneurs flood into markets the year (or six months) after positive events (the smallest unit in the analyses), while events two periods prior do not have a detectable effect.30

Numerous examples illustrate this rapid-updating process. Technology enthusiasts might remember Alta Vista, Northern Light, FAST Search, or Lycos–firms that specialized in searching the World Wide Web during the 1990s. After a spate of failures, many observers declared that the search category was not viable, and new entries into the search category fell off sharply. Yet within a short time, the fantastic success of Google would reverse the impression of search. Post-Google, search is not only viewed as a lucrative market, but is regarded by many as

30 VC fundings in one year are correlated with fundings in subsequent years, as the tests of hypothesis 1b show, so the same market may be “hot” for multiple years. What this finding shows is that the statistical effect on entry is due to the previous year’s events.
the ideal online advertisement-based business. Another iconic example is the Apple Newton, a hand-held device released in the 1990s that in many ways anticipated the iPhone. The Newton’s failure quickly stigmatized the market for “smart, handheld devices,” making similar innovations taboo for a number of years. Later, the overwhelming success of the iPhone suddenly reversed this consensus. Similar discrete changes—for better or for worse—can be seen over time in markets such as artificial intelligence, data compression, embedded operating systems, online grocery delivery, social networks, and the list goes on. Perceptions of a market’s potential (or peril) change rapidly over time as people react to the limited but socially magnified information provided by vital events.

Our interviews also indicate that VCs look for sudden changes in market dynamics, which reinforces this process. As one VC states: “You want to have a market insight which could be [that] there’s a sudden shift in the way things are being distributed and so therefore a new company will emerge in this space.” Another adds, “[A hot market] means it’s a market space that’s ripe for rapid adoption. The time has come for that solution in that market, and it’s a huge market that they’re going to be able to very quickly grow into.” VCs closely track changes in the prospects of the market categories their investments are in. One explained, “One of the first questions [a prominent investor] asks in board meetings is ‘what has happened to the market, that has either made the market bigger or more attractive, or has shrunk the market and made it less attractive.’” This underscores the expectation that a market’s prospects can and will change rapidly, an assumption that leads both entrepreneurs and investors to constantly scan the landscape for more fertile markets to engage in. Keying in on vital events justifies a firm’s ongoing presence in a market, or their decision to enter a new, more promising area.
Our focus on vital events demonstrates merit in paying more attention to discrete shifts in market dynamics. Models of diffusion and population dynamics typically describe change as gradual over time. Even the “wave” metaphor intimates an incremental process of growth and decline. Yet we know that many forms of change in industrial evolution occur suddenly, accompanied by a re-thinking of collective understandings. Vital events, broadcast through the media and widely discussed, may lead to faster changes. The popular press often features discussions of “disruptive” change, complete with conferences where pundits gather to discuss the “new new thing.” Our work demonstrates that existing models can benefit from explicit theorizing about the way that discrete events create dramatic shifts in firm behavior.

Our study does not suggest that search in itself is problematic for entrepreneurs. Entrepreneurs test out new ideas and often discover a market for their novel products through a process of trial and error. Entrepreneurial search is necessary if a company is failing to gain traction. Our study does suggest that some search processes are more productive than others. Search makes entrepreneurs susceptible to consensus behavior, which is detrimental. What underlies the problem is that moves into promising markets are less scrutinized. Managers overweigh the promise of the hot market and under-weigh the ability of their firm to serve that market. It is possible that entrepreneurs can curb this tendency and make market search more productive, by taking into account people’s natural tendency to scrutinize areas that are out of vogue and to less comprehensively examine consensus moves. Entrepreneurs deliberately gather data on where VCs are investing to inform market entry decisions. Adding a formal requirement to carefully analyze product-market fit in addition to market potential—perhaps by assigning an executive to a “devil’s advocate” role—may help offset these tendencies.
Of course, the viability of a market is critical to the success of any firm. Entrepreneurs who are well positioned to dominate a high-potential market would be wise to make the consensus move. In our model, hazards from consensus entry—and benefits of non-consensus entry—result because of changes in the average viability of firms that enter following vital events. Conditional on being viable in a market category, it is beneficial to be in a better market. The problem that arises is that it is difficult to engage in a sober analysis of product-market fit in the midst of market hype. This is where additional scrutiny is important. Entrepreneurial teams that are tempted to enter hot markets should wrestle with the question: if the company is so well positioned to dominate that category, why were they not there already?

Our results support the hypothesis that positive vital events attract entry, but there is no evidence that bankruptcies deter entry. This is surprising in light of previous research that negative signals are stronger than positive ones (Baumeister, Bratslavsky, and Vohs, 2001), and that stigma readily spreads in markets (Jonsson, Greve, and Fujiwara-Grev, 2009; Pontikes, Negro, and Rao, 2010). We do find a negative effect of previous market exits on future entry. Exits also can capture that a market category has become tainted. The difference between bankruptcies and exits may be that bankruptcies free up resources in a market. This leads to two opposing forces: one where the market becomes stigmatized and so potential entrants stay away, and the other where bankruptcies create excess capacity that can be purchased inexpensively. The combination may lead to the observed effect, where the null cannot be rejected. We do find that firms entering a market after bankruptcies are more likely to stay. This supports the idea, expressed in our interviews, that entrants face higher scrutiny in the wake of negative events—even if it does not translate to lower entry rates.
Our results complement Nanda and Rhodes-Kropf (2013), who investigate outcomes for firms funded in hot *time periods*, when many other firms are receive funding. They find that these firms are more likely to fail, not because they are worse, but because they are riskier. Firms funded in hot times are also more likely to have a high-valuation IPO. They show this is due to increases in available capital during these periods. Our study investigates effects of herding into hot *market categories*, holding years constant, so there is no difference in available capital. This suggests that a social process underlies the dynamic. Given the same temporal conditions, entrepreneurs or VCs may choose either a consensus strategy, following the crowd into market categories, or a non-consensus strategy, staking out a unique and perhaps unpopular position. At the same point in time, consensus behavior, in terms of *where* an entrepreneur chooses to position or VC chooses to invest, has adverse outcomes.

Previous research on herding processes, or diffusion more generally, typically focuses on changes in adoption over time in one market, and does not investigate long-term effects of consensus behavior (Delacroix and Carroll, 1983; Greve, 1996; Strang and Soule, 1998). Research on long-term effects of founding conditions looks at density at entry in a particular market (Carroll and Hannan, 1989; Swaminathan, 1996; Barnett et al., 2003), but does not explain why density is high at a given time. Our research design allows us to study both topics. We have gathered data on hundreds of market categories over time. Rather than assume that entrepreneurs stay in the market in which they are founded, these rich data allow us to study the process of entrepreneurial search, where firms enter and exit categories, looking for the right place to position their products. We also link these data to VC fundings and bankruptcies in market categories, and so directly measure vital events that create consensus. We first document herding processes that result from consensus views. Next, we study long-term consequences and
find adverse effects of consensus behavior. Whereas other research analyzes temporal changes in one market (at a time), our test simultaneously analyzes hundreds of market categories in an industry over a period of thirteen years.

In our model, positive vital events lead to increases in density at entry. This is because perceptions of munificence effectively lower the selection threshold, resulting in a flood of new entrants with lower average viability. In our context, the effect of herding is so strong that fundings and density are highly correlated and independent effects cannot be estimated. More generally, high density often reflects market exuberance, and density should not be taken only to indicate competition. Our measure of positive vital events is a less ambiguous signal. It may be interesting for future researchers to find a context where the competitive effect can be identified distinctly from market exuberance.

There is a paradox in entrepreneurial markets: what promotes market growth is perilous for organizations entering that market. Positive events indicate a market is promising and draw a host of entries—including those whose offerings do not fit well. Over time, market hype subsides and consensus organizations find themselves in an area where they have low market fit. These organizations are unlikely to be funded and are increasingly likely to exit. Positive events also draw a flood of venture capital investment, which sets into motion a similar process. Less viable organizations get funded, and the hype results in more competitors than warranted for long-term demand. Organizations first funded under these conditions are less likely to IPO. In markets that are stigmatized, entrants benefit from having to undergo high scrutiny before entering. This keeps away all organizations but those with the best market fit, which are positioned to succeed. Although consensus actions may seem to be the safe bet, it may be non-consensus behavior that is the more sustainable strategy.
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Strang, D. and S. Soule  

Sujan, M  

Sutton, R. I. and A. L. Callahan  

Swaminathan, A.  

Theil, P.  

Tyebjee, T. and A. Bruno  

Valliere, D. and R. Peterson  

Venkataraman, S.  

Wang, P.  

Weick, K.  

White, H.  

Yue, L. Q.  
## Tables

**Table 1. Descriptive Statistics for Market Category Entry Analysis**

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organization enters market category</td>
<td>0.0019</td>
<td>0.0431</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>VC fundings in market (weighted; logged)</td>
<td>0.2571</td>
<td>0.4439</td>
<td>0</td>
<td>3.261</td>
</tr>
<tr>
<td>Bankruptcies in market (weighted)</td>
<td>0.0152</td>
<td>0.1095</td>
<td>0</td>
<td>1.667</td>
</tr>
<tr>
<td>No. members of market (weighted; logged)</td>
<td>1.155</td>
<td>0.9723</td>
<td>0</td>
<td>5.105</td>
</tr>
<tr>
<td>No. entries into market (weighted; logged)</td>
<td>0.7769</td>
<td>0.7878</td>
<td>0</td>
<td>4.474</td>
</tr>
<tr>
<td>No. exits from market (weighted; logged)</td>
<td>0.7020</td>
<td>0.7815</td>
<td>0</td>
<td>4.642</td>
</tr>
<tr>
<td>Leniency of market</td>
<td>1.410</td>
<td>0.9927</td>
<td>0</td>
<td>4.063</td>
</tr>
<tr>
<td>No. Software 500-ranked orgs in market (weighted; logged)</td>
<td>0.3594</td>
<td>0.5298</td>
<td>0</td>
<td>3.489</td>
</tr>
<tr>
<td>No. patenting orgs in market (weighted; logged)</td>
<td>0.3297</td>
<td>0.4985</td>
<td>0</td>
<td>3.184</td>
</tr>
<tr>
<td>Age of market (since 1990)</td>
<td>5.812</td>
<td>3.671</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Technical proximity of organization to market</td>
<td>0.0008</td>
<td>0.0176</td>
<td>0</td>
<td>2.447</td>
</tr>
<tr>
<td>No. organization's patents (prev year; logged)</td>
<td>0.0675</td>
<td>0.2949</td>
<td>0</td>
<td>3.091</td>
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<tr>
<td>No. markets organization is in (logged)</td>
<td>0.7156</td>
<td>0.6094</td>
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<td>2.833</td>
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<td>Organization ranked in Software 500</td>
<td>0.0557</td>
<td>0.2294</td>
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<td>1</td>
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<tr>
<td>Organization received VC funding</td>
<td>0.1146</td>
<td>0.3185</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Time since last entered a market</td>
<td>0.7768</td>
<td>1.147</td>
<td>0</td>
<td>10</td>
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<tr>
<td>Organization tenure (since 1990)</td>
<td>1.676</td>
<td>1.890</td>
<td>0</td>
<td>13</td>
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<tr>
<td>Autoregression control</td>
<td>0.0019</td>
<td>0.0034</td>
<td>0</td>
<td>0.0320</td>
</tr>
<tr>
<td>Year</td>
<td>1999</td>
<td>2.580</td>
<td>1990</td>
<td>2002</td>
</tr>
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</table>

1 Data contain 1,335,633 potential organization-market dyads over the years 1990 through 2002. There are 6,537 market entries across 3,505,317 organization-market-years. Data include private organizations, age ≤ 12 or where founding date is not known. All independent variables are lagged; (prev year) is specified in some instances for clarity.
<table>
<thead>
<tr>
<th>Model</th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
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<tr>
<td>VC fundings in market (weighted; logged)</td>
<td>0.250***</td>
<td>0.225***</td>
<td>0.167***</td>
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<tr>
<td></td>
<td>(0.0657)</td>
<td>(0.0667)</td>
<td>(0.0431)</td>
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<td>&lt; 2 VC funding in market</td>
<td></td>
<td></td>
<td></td>
<td>0.259***</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0633)</td>
<td></td>
</tr>
<tr>
<td>[2, 15) VC fundings in market</td>
<td></td>
<td></td>
<td></td>
<td>0.457***</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0893)</td>
<td></td>
</tr>
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<td>15+ VC fundings in market</td>
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<td></td>
<td>0.763***</td>
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<tr>
<td>Bankruptcies in market (weighted)</td>
<td>0.143+</td>
<td></td>
<td></td>
<td>0.0851</td>
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<tr>
<td></td>
<td>(0.0847)</td>
<td></td>
<td></td>
<td>(0.0552)</td>
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<td>Select Controls</td>
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</tr>
<tr>
<td>No. members of market (weighted; logged)</td>
<td>0.289**</td>
<td>0.331***</td>
<td>0.331***</td>
<td>0.269**</td>
<td>0.132+</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.0964)</td>
<td>(0.0936)</td>
<td>(0.0970)</td>
<td>(0.0698)</td>
</tr>
<tr>
<td>No. entries into market (weighted; logged)</td>
<td>0.892***</td>
<td>0.745***</td>
<td>0.750***</td>
<td>0.806***</td>
<td>0.400***</td>
</tr>
<tr>
<td></td>
<td>(0.112)</td>
<td>(0.104)</td>
<td>(0.105)</td>
<td>(0.103)</td>
<td>(0.0591)</td>
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<tr>
<td>No. exits from market (weighted; logged)</td>
<td>-0.227*</td>
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<td>-0.243**</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.0981)</td>
<td>(0.0939)</td>
<td>(0.0880)</td>
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<td></td>
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<tr>
<td>No. exits from market (excl bankrupt)</td>
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<td></td>
<td>-0.294**</td>
<td>-0.279***</td>
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<td>(0.0941)</td>
<td>(0.0467)</td>
</tr>
<tr>
<td>Leniency of market</td>
<td>0.407***</td>
<td>0.399***</td>
<td>0.402***</td>
<td>0.374***</td>
<td>0.0655*</td>
</tr>
<tr>
<td></td>
<td>(0.0349)</td>
<td>(0.0329)</td>
<td>(0.0330)</td>
<td>(0.0366)</td>
<td>(0.0316)</td>
</tr>
<tr>
<td>Autoregression control</td>
<td>100.2***</td>
<td>100.4***</td>
<td>100.4***</td>
<td>100.3***</td>
<td>100.7***</td>
</tr>
<tr>
<td></td>
<td>(2.087)</td>
<td>(2.084)</td>
<td>(2.083)</td>
<td>(2.078)</td>
<td>(2.373)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Category dummies</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Log pseudo likelihood</td>
<td>-33,615.0</td>
<td>-33,584.8</td>
<td>-33,581.6</td>
<td>-33,576.3</td>
<td>-32723.8</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>27</td>
<td>28</td>
<td>29</td>
<td>30</td>
<td>473</td>
</tr>
</tbody>
</table>

+ p < 0.10 * p < 0.05 ** p < 0.01 *** p < 0.001

1. Data contain 1,335,633 potential organization-market dyads from 1990 through 2002, with 6,537 market entries across 3,505,317 organization-market-years. Data include private organizations, age ≤12 or where founding date is not known. All models include controls for: the age of the market (since 1990), the number of markets the organization is in (logged), whether the organization was ranked in the Software 500 (prev year), whether the organization received VC funding (prev year), time since the organization last entered any market, and organization tenure (since 1990). Duration pieces for 0-1, 1 – 2, 2 – 4, and 4+ years are included. All independent variables are lagged.
Table 3. Models of the Market Category Entry Rate by Software Firms (age ≤12; private)\(^1\)

<table>
<thead>
<tr>
<th></th>
<th>(1) 1-year spells</th>
<th>(2) 6-month spells</th>
<th>(3) 1-year spells</th>
<th>(4) 1-year spells</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC fundings in market, prev period (weighted; logged)</td>
<td>0.221**</td>
<td>0.156**</td>
<td>0.227***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0709)</td>
<td>(0.0525)</td>
<td>(0.0645)</td>
<td></td>
</tr>
<tr>
<td>VC fundings in market - 2 periods prior (weighted; logged)</td>
<td>0.0610</td>
<td>0.0564</td>
<td></td>
<td>0.244***</td>
</tr>
<tr>
<td></td>
<td>(0.0499)</td>
<td>(0.0539)</td>
<td></td>
<td>(0.0646)</td>
</tr>
<tr>
<td>Fundings in market: all other VCs (weighted; logged)</td>
<td></td>
<td></td>
<td></td>
<td>0.244***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0975)</td>
</tr>
<tr>
<td>Fundings in market: low-status VCs (weighted; logged)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Select Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. members of market (weighted; logged)</td>
<td>0.323**</td>
<td>0.514***</td>
<td>0.255*</td>
<td>0.335***</td>
</tr>
<tr>
<td></td>
<td>(0.0989)</td>
<td>(0.0576)</td>
<td>(0.102)</td>
<td>(0.0984)</td>
</tr>
<tr>
<td>No. entries into market (weighted; logged)</td>
<td>0.757***</td>
<td>0.517***</td>
<td>0.732***</td>
<td>0.745***</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.0648)</td>
<td>(0.103)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>No. exits from market (weighted; logged)</td>
<td>-0.308**</td>
<td>-0.131**</td>
<td>-0.305**</td>
<td>-0.289**</td>
</tr>
<tr>
<td></td>
<td>(0.0939)</td>
<td>(0.0464)</td>
<td>(0.0961)</td>
<td>(0.0921)</td>
</tr>
<tr>
<td>Leniency of market</td>
<td>0.398***</td>
<td>0.444***</td>
<td>0.400***</td>
<td>0.400***</td>
</tr>
<tr>
<td></td>
<td>(0.0326)</td>
<td>(0.0307)</td>
<td>(0.0344)</td>
<td>(0.0330)</td>
</tr>
<tr>
<td>Autoregression control</td>
<td>100.4***</td>
<td>147.9***</td>
<td>100.2***</td>
<td>100.3***</td>
</tr>
<tr>
<td></td>
<td>(2.082)</td>
<td>(2.315)</td>
<td>(2.083)</td>
<td>(2.081)</td>
</tr>
<tr>
<td>No. Software 500-ranked org in market (weighted; logged)</td>
<td></td>
<td></td>
<td></td>
<td>0.0619</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0551)</td>
</tr>
<tr>
<td>No. patenting orgs in market (weighted; logged)</td>
<td></td>
<td></td>
<td></td>
<td>0.128*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0634)</td>
</tr>
<tr>
<td>Technical proximity of organization to market</td>
<td></td>
<td></td>
<td></td>
<td>0.628**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.238)</td>
</tr>
<tr>
<td>No. organization's patents (prev year; logged)</td>
<td></td>
<td></td>
<td></td>
<td>0.00274</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0397)</td>
</tr>
<tr>
<td>Year / 6-month dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Log pseudo likelihood</td>
<td>-33,583.0</td>
<td>-38,656.6</td>
<td>-33,568.0</td>
<td>-33,585.1</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>29</td>
<td>42</td>
<td>32</td>
<td>29</td>
</tr>
</tbody>
</table>

\(+p<.10 *p<.05 **p<.01 *** p<0.001\)

\(^1\) Data for yearly spell models contain 1,335,633 potential organization-market dyads from 1990 through 2002, with 6,537 market entries across 3,505,317 organization-market-years. 6-month spell models contain 1,312,184 potential organization-market dyads from 1990 through 2002, with 7,271 market entries across 5,851,497 organization-market-periods. Data include private organizations, age ≤12 or where founding date is not known. All models include controls for: the age of the market (since 1990), the number of markets the organization is in (logged), whether the organization was ranked in the Software 500 (prev year), whether the organization received VC funding (prev year), time since the organization last entered any market, and organization tenure (since 1990). Duration pieces for 0-1, 1–2, 2–4, and 4+ years are included. All independent variables are lagged; (prev year) is specified in some instances for clarity.
Table 4. Descriptive Statistics for Venture Capital Funding Analysis

<table>
<thead>
<tr>
<th>Description</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Org receives VC funding</td>
<td>0.1449</td>
<td>0.3520</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>No. categories entered after 2+ VC fundings (2 yr window; logged)</td>
<td>0.1094</td>
<td>0.3099</td>
<td>0</td>
<td>2.398</td>
</tr>
<tr>
<td>No. categories entered and exited in the previous year</td>
<td>0.3922</td>
<td>0.9090</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>VC fundings in market (prev year)</td>
<td>2.782</td>
<td>3.935</td>
<td>0</td>
<td>25.07</td>
</tr>
<tr>
<td>Fuzziness of organization’s markets</td>
<td>0.3633</td>
<td>0.2760</td>
<td>0</td>
<td>0.8332</td>
</tr>
<tr>
<td>No. members of organization’s markets (weighted; logged)</td>
<td>2.296</td>
<td>1.922</td>
<td>0</td>
<td>6.549</td>
</tr>
<tr>
<td>Org's tenure in data</td>
<td>1.742</td>
<td>1.956</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>No. organization's patents (prev year)</td>
<td>0.1641</td>
<td>0.9623</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>No. acquisitions (prev year)</td>
<td>0.0077</td>
<td>0.0946</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>No. previous VC funding rounds</td>
<td>0.6412</td>
<td>1.6528</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Organization ranked in Software 500 (prev year)</td>
<td>0.0581</td>
<td>0.2339</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Year</td>
<td>1998</td>
<td>2.968</td>
<td>1990</td>
<td>2002</td>
</tr>
</tbody>
</table>

1 Data contain 3,551 organizations across 10,538 organization-years, experiencing 1,527 VC funding events, between 1990 and 2002. Data include private organizations, age < 15 or where founding date is not known. All independent variables are lagged; (prev year) is specified in some instances for clarity.
Table 5. Models of the VC Funding Rate for Software Organizations¹

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. categories entered after 2+ VC fundings (2 year window; logged)</td>
<td>-0.261* (0.107)</td>
<td>-0.251* (0.110)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. categories entered and exited in the previous year</td>
<td></td>
<td></td>
<td>-0.0173 (0.0299)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VC fundings in market (prev year)</td>
<td>0.0412* (0.0182)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VC fundings in market (prev year) sq</td>
<td>-0.0028** (0.0011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;2 VC fundings in market</td>
<td>0.200+ (0.107)</td>
<td>0.194+ (0.107)</td>
<td>0.192+ (0.107)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[2-15) VC fundings in market</td>
<td>0.286** (0.111)</td>
<td>0.279* (0.111)</td>
<td>0.275* (0.111)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15+ VC fundings in market</td>
<td>-0.0597 (0.190)</td>
<td>-0.0760 (0.189)</td>
<td>-0.0829 (0.189)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuzziness of organization’s markets</td>
<td>1.346*** (0.224)</td>
<td>1.357*** (0.226)</td>
<td>1.323*** (0.227)</td>
<td>1.180*** (0.234)</td>
<td>1.179*** (0.234)</td>
</tr>
<tr>
<td>No. members of organization’s markets (weighted; logged)</td>
<td>0.0534+ (0.0292)</td>
<td>0.0456 (0.0294)</td>
<td>0.0461 (0.0294)</td>
<td>0.0715* (0.0318)</td>
<td>0.0772* (0.0324)</td>
</tr>
<tr>
<td>Org’s tenure in data</td>
<td>-0.0666* (0.0282)</td>
<td>-0.0642* (0.0285)</td>
<td>-0.0638* (0.0283)</td>
<td>-0.0449 (0.0284)</td>
<td>-0.0479 (0.0292)</td>
</tr>
<tr>
<td>No. organization’s patents (prev year)</td>
<td>0.0151 (0.0230)</td>
<td>0.0158 (0.0227)</td>
<td>0.0162 (0.0230)</td>
<td>0.0151 (0.0228)</td>
<td>0.0145 (0.0229)</td>
</tr>
<tr>
<td>No. acquisitions (prev year)</td>
<td>0.0305 (0.296)</td>
<td>0.0304 (0.297)</td>
<td>0.0298 (0.295)</td>
<td>0.0384 (0.305)</td>
<td>0.0502 (0.309)</td>
</tr>
<tr>
<td>No. previous VC funding rounds</td>
<td>0.165*** (0.0278)</td>
<td>0.166*** (0.0275)</td>
<td>0.167*** (0.0275)</td>
<td>0.169*** (0.0262)</td>
<td>0.169*** (0.0262)</td>
</tr>
<tr>
<td>Organization ranked in Software 500 (prev year)</td>
<td>-0.163 (0.158)</td>
<td>-0.175 (0.158)</td>
<td>-0.179 (0.158)</td>
<td>-0.174 (0.158)</td>
<td>-0.171 (0.158)</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pseudo log likelihood</td>
<td>-3979.5</td>
<td>-3975.8</td>
<td>-3974.0</td>
<td>-3970.2</td>
<td>-3970.0</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>23</td>
<td>25</td>
<td>26</td>
<td>27</td>
<td>28</td>
</tr>
</tbody>
</table>

+ p<.10 * p<.05 ** p<.01 *** p<.001
1 Data contain 3,551 organizations across 10,538 organization-years, experiencing 1,527 VC funding events. Data include private organizations, age < 15 or where founding date is not known. All independent variables are lagged; (prev year) is specified in some instances for clarity. Year dummies and duration pieces for: 0-1 year, 1-3 years, 3-5 years, and 5+ years included in all models. All independent variables are lagged; (prev year) is specified in some instances for clarity.
Table 6. Descriptive Statistics for Market Category Exit Analysis\(^1\)

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organization exits category</td>
<td>0.3284</td>
<td>0.4696</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>VC fundings in category at time of entry (weighted; logged)</td>
<td>0.7625</td>
<td>0.8290</td>
<td>0</td>
<td>3.261</td>
</tr>
<tr>
<td>Bankruptcies in category at time of entry (weighted)</td>
<td>0.0431</td>
<td>0.1844</td>
<td>0</td>
<td>1.107</td>
</tr>
<tr>
<td>VC fundings in category (weighted; logged; prev year)</td>
<td>0.8679</td>
<td>0.8704</td>
<td>0</td>
<td>3.261</td>
</tr>
<tr>
<td>Bankruptcies in category (weighted; prev year)</td>
<td>0.0553</td>
<td>0.2080</td>
<td>0</td>
<td>1.107</td>
</tr>
<tr>
<td>No. members of category (weighted; logged)</td>
<td>2.468</td>
<td>1.258</td>
<td>0</td>
<td>5.105</td>
</tr>
<tr>
<td>No. entries into category (weighted; logged)</td>
<td>1.912</td>
<td>1.173</td>
<td>0</td>
<td>4.474</td>
</tr>
<tr>
<td>No. exits from category (weighted; logged)</td>
<td>1.634</td>
<td>1.178</td>
<td>0</td>
<td>4.397</td>
</tr>
<tr>
<td>Leniency of category</td>
<td>2.112</td>
<td>0.8994</td>
<td>0</td>
<td>4.046</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>6.788</td>
<td>3.262</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>No. categories organization is in (logged)</td>
<td>0.8066</td>
<td>0.6671</td>
<td>0</td>
<td>2.639</td>
</tr>
<tr>
<td>Organization ranked in Software 500 (prev year)</td>
<td>0.0708</td>
<td>0.2566</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Organization received VC funding (prev year)</td>
<td>0.1334</td>
<td>0.3400</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Time since last exited a category</td>
<td>0.5938</td>
<td>1.057</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Organization tenure (since 1990)</td>
<td>1.621</td>
<td>1.771</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Autoregression control</td>
<td>0.3062</td>
<td>0.3841</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Year</td>
<td>1998</td>
<td>2.733</td>
<td>1990</td>
<td>2001</td>
</tr>
</tbody>
</table>

\(^1\) Data contain 12,026 organization-market dyads over the years 1990 through 2001. There are 6,738 market exits across 19,437 organization-market-years. Data include private organizations, age ≤ 12 or where founding date is not known. All independent variables are lagged; (prev year) is specified in some instances for clarity.
Table 7. Models of the Market Category Exit Rate by Software Firms (age ≤12; private)¹

<table>
<thead>
<tr>
<th>Duration [0-2] years</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>Bankruptcies in market at entry:</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration [2-4] years</td>
<td></td>
<td>(0.0744)</td>
<td>(0.0738)</td>
<td>-0.556+</td>
<td>(0.298)</td>
<td>(0.367)</td>
<td>(0.258)</td>
</tr>
<tr>
<td>Duration 4+ years</td>
<td></td>
<td>(0.262)</td>
<td>(0.756)</td>
<td>(0.189)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VC fundings in market at entry: prev year</td>
<td>(0.371)</td>
<td>(0.0343)</td>
<td>(0.0404)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration [0-2] years</td>
<td></td>
<td>(0.00751)</td>
<td>(0.00381)</td>
<td>0.192</td>
<td>(0.122)</td>
<td>(0.122)</td>
<td>(0.0955)</td>
</tr>
<tr>
<td>Duration [0-4] years</td>
<td></td>
<td>(0.0815)</td>
<td>(0.0663)</td>
<td>(0.0934)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration 4+ years</td>
<td></td>
<td>(0.122)</td>
<td>(0.122)</td>
<td>(0.0955)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Select Controls

| No. members of market (weighted; logged) |      | (0.0570) | (0.0675) | (0.0564) |
| No. entries into market (weighted; logged) |      | (0.0485) | (0.0534) | (0.0472) |
| No. exits from market (weighted; logged) |      | (0.0556) | (0.0445) | (0.0546) |
| Autoregression control |      | (0.0336) | (0.0375) | (0.0336) |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cat dummies | No | Yes | No | Cat dummies | No | Yes | No |
| Log pseudolikelihood | -12,219.1 | -11,914.1 | -12219.6 | Log pseudolikelihood | -12,219.3 | -11,914.1 | -12,219.9 |
| Degrees of freedom | 32 | 439 | 32 | Degrees of freedom | 30 | 438 | 30 |

¹ Data contain 12,026 organization-market dyads over the years 1990 through 2001. There are 6,738 market exits across 19,437 organization-market-years. Data include private organizations, age ≤ 12 or where founding date is not known. All models include controls for: market leniency, age of market (since 1990), number of markets the organization is in (logged), whether the organization was ranked in the Software 500 (prev year), whether the organization received VC funding (prev year), time since the organization last exited any market, organization tenure (since 1990). Duration pieces for: 0-1 year, 1-2 years, 2-4 years, and 4+ years are included. All independent variables are lagged.

\*p<.10  \*\*p<.05  \*\*\*p<.01  \*\*\*\*p<.001
Table 8. Descriptive Statistics for IPO Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organization goes public (IPO)</td>
<td>0.0302</td>
<td>0.1710</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>VC fundings in market(s) at round 1 funding</td>
<td>0.2342</td>
<td>1.464</td>
<td>0</td>
<td>25.07</td>
</tr>
<tr>
<td>VC fundings in market(s) at round 1 funding (logged)</td>
<td>0.0765</td>
<td>0.3554</td>
<td>0</td>
<td>3.261</td>
</tr>
<tr>
<td>VC fundings in market(s), average over all fundings</td>
<td>0.5450</td>
<td>2.034</td>
<td>0</td>
<td>25.07</td>
</tr>
<tr>
<td>No. members of organization’s markets (weighted, logged)</td>
<td>2.397</td>
<td>1.899</td>
<td>0</td>
<td>6.549</td>
</tr>
<tr>
<td>No. markets organization is in (logged)</td>
<td>0.7462</td>
<td>0.5969</td>
<td>0</td>
<td>2.890</td>
</tr>
<tr>
<td>Received VC funding</td>
<td>0.1340</td>
<td>0.3407</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of funding rounds</td>
<td>0.6110</td>
<td>1.6453</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Organization has patented</td>
<td>0.1249</td>
<td>0.3307</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Organization ranked in Software 500</td>
<td>0.0717</td>
<td>0.2579</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Year</td>
<td>1998.17</td>
<td>2.930</td>
<td>1990</td>
<td>2002</td>
</tr>
</tbody>
</table>

¹ These data include 3,633 organizations over 11,805 organization-years with 356 IPO events over the years 1990-2002. Data include private organizations, age ≤ 20 or where founding date is not known, and exclude organizations that enter the data the year they IPO. All independent variables are lagged.
Table 9. Models of the IPO Rate by Software Firms

<table>
<thead>
<tr>
<th>Model Description</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC fundings in market(s), average over all fundings</td>
<td>All orgs: -0.0401</td>
<td>All orgs: -0.0898+</td>
<td>All orgs: -0.131*</td>
<td>Funded: -0.185</td>
<td>All orgs: -0.185</td>
<td>Funded: -0.335*</td>
</tr>
<tr>
<td></td>
<td>(0.0437)</td>
<td>(0.0533)</td>
<td>(0.0584)</td>
<td></td>
<td>(0.151)</td>
<td>(0.161)</td>
</tr>
<tr>
<td>VC fundings in market(s) at round 1 funding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VC fundings in market(s) at round 1 funding (logged)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. members of organization’s markets (weighted, logged)</td>
<td>-0.162**</td>
<td>-0.145*</td>
<td>-0.158*</td>
<td>-0.181+</td>
<td>-0.160**</td>
<td>-0.186+</td>
</tr>
<tr>
<td></td>
<td>(0.0608)</td>
<td>(0.0636)</td>
<td>(0.0612)</td>
<td>(0.106)</td>
<td>(0.0610)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>No. markets organization is in (logged)</td>
<td>0.634***</td>
<td>0.599***</td>
<td>0.613***</td>
<td>0.663*</td>
<td>0.623***</td>
<td>0.689*</td>
</tr>
<tr>
<td></td>
<td>(0.171)</td>
<td>(0.176)</td>
<td>(0.172)</td>
<td>(0.286)</td>
<td>(0.172)</td>
<td>(0.284)</td>
</tr>
<tr>
<td>Received VC funding</td>
<td>0.857***</td>
<td>0.965***</td>
<td>1.001***</td>
<td>0.988***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.195)</td>
<td>(0.177)</td>
<td>(0.189)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of funding rounds</td>
<td>0.0630*</td>
<td>0.0604*</td>
<td>0.0484+</td>
<td>0.0145</td>
<td>0.0496+</td>
<td>0.0105</td>
</tr>
<tr>
<td></td>
<td>(0.0275)</td>
<td>(0.0277)</td>
<td>(0.0294)</td>
<td>(0.0356)</td>
<td>(0.0301)</td>
<td>(0.0368)</td>
</tr>
<tr>
<td>Organization has patented</td>
<td>0.712***</td>
<td>0.716***</td>
<td>0.715***</td>
<td>0.652***</td>
<td>0.711***</td>
<td>0.642***</td>
</tr>
<tr>
<td></td>
<td>(0.117)</td>
<td>(0.117)</td>
<td>(0.117)</td>
<td>(0.187)</td>
<td>(0.117)</td>
<td>(0.188)</td>
</tr>
<tr>
<td>Organization ranked in Software 500</td>
<td>0.751***</td>
<td>0.753***</td>
<td>0.784***</td>
<td>0.982***</td>
<td>0.776***</td>
<td>0.977***</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.142)</td>
<td>(0.234)</td>
<td>(0.143)</td>
<td>(0.236)</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pseudo log likelihood</td>
<td>-924.1</td>
<td>-923.6</td>
<td>-922.4</td>
<td>-307.5</td>
<td>-923.3</td>
<td>-308.3</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>23</td>
<td>24</td>
<td>24</td>
<td>23</td>
<td>24</td>
<td>23</td>
</tr>
</tbody>
</table>

+p<.10 *p<.05 **p<.01

1 Data for all (age ≤ 20) contain 3,633 organizations over 11,805 organization-years with 356 IPO events. Data for funded contain 642 organizations (age ≤ 20) that received funding after appearing in the press release data over 1,582 years, with 129 IPO events. Year dummies and duration pieces for: 0-1 year, 1-3 years, 3-5 years, 5-7 years, and 7+ years (5+ years for funded only). All independent variables are lagged.
Figures

Figure 1. Predicted Effects of VC Funding for All Organizations and Organizations that "Chase" Funding.¹

¹Based on results from table 5 column (4).
Figure 2. Predicted Effects of Entry After Vital Events on the Organization’s Market Category Exit Rate

Based on results from table 7 column 4.