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The Non-consensus Entrepreneur: Organizational Responses to Vital Events

Elizabeth G. Pontikes[1] and William P. Barnett[2]

Abstract
Salient successes and failures, such as spectacular venture capital investments or agonizing bankruptcies, affect collective beliefs about the viability of particular markets. Using data on software start-ups from 1990 to 2002, we show that collective sense-making in the wake of such vital events can result in consensus behavior among entrepreneurs. Market search is a critical part of the entrepreneurial process, as entrepreneurs frequently enter new markets to find high-growth areas. 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. When notorious failures render a market unpopular, only the most viable entrants will overcome exaggerated skepticism and enter, taking the non-consensus route. Venture capitalists likewise 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. We find that consensus entrants are less viable, while non-consensus entrants are more likely to prosper. Non-consensus entrepreneurs who buck the trends are most likely to stay in the market, receive funding, and ultimately go public.

Keywords: organizational ecology, entrepreneurship, venture capital, markets, categories, market entry, consensus, market search

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,

[1] Booth School of Business, University of Chicago
[2] Graduate School of Business, Stanford University

2010). But much interest in entrepreneurship surrounds how start-up 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 which focuses 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). But we conceive of market entry as a selection process in which high-profile successes and failures lead to different levels of scrutiny in the decision to enter a market. Our model implies that conforming to the consensus view can be detrimental and that there are advantages to non-consensus actions.

Drawing on interviews we conducted with entrepreneurs and venture capitalists (VCs), as well as popular and academic literature, we found 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 successes and failures—are important social cues that influence 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, with non-consensus entrepreneurs realizing more-favorable outcomes.

[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 (Stuart and Sorenson, 2005; Ruef, 2010). 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 submarkets as categorical systems that group organizations and products (Sujan, 1985; Porac and Thomas, 1990; Hannan, Pólos, and Carroll, 2007; Pontikes and Barnett, 2015).

To investigate these ideas, we look at software entrepreneurs. The software industry is characterized by many market categories, or submarkets, that segment the domain. There were 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, and we investigate the 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. Blank (2013: 89) gave 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.'' Common wisdom in the tech industry claims that this ''painful, soul-searching'' process is critical for entrepreneurial success (Blank, 2013: 89; Ries, 2011).

Our interviews reinforce this view, suggesting that entrepreneurs actively engage in market search. As one venture capitalist stated, ''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 described the process this way:

> 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 stipulated 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 added, ''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, it 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 in which 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 in which the firm can gain traction.

This search process is resonant with the literature on organizational change. Levinthal and March (1981) proposed a model of adaptive learning in which organizations search for new technologies when performance falls below aspiration levels, and the opportunities sampled depend on the current technology. White (1981) argued 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 during which 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 the data we collected, 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 percent 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 in which 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; he or she is creating an organization in which multiple people need to agree on a course of 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 described it:

> 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

[3] These statistics are reported on organizations that appear for more than one year.

> 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. Thus 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 judgment is influenced by whether others outside the company, especially highly regarded individuals, believe that the market category is "hot." One entrepreneur stated, "The big thing for [our company] is that the market potential in this new market is much, much bigger than [the old market]." Another said 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 offsite 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 (e.g., Davis, 1991; Greve, 1996; Carroll and Hannan, 2000; Rao, Greve, and Davis, 2001). 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, but vital events can also play a catalyzing role. 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) showed 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). One VC we interviewed described having to repeatedly defend the 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, which 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 explained:

> 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.''

Because a general industry consensus develops from vital events about the perceived promise or peril of a market, we expect them 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, and 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 (H1a): The greater the number of positive (or negative) vital events in a market category, the greater (or 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 typically they are not. 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, which may explain the strong social comparisons that have been observed among VC firms (Sorenson and Stuart, 2008).

Consequently, we expect that 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. Their tendency to invest in ''hot markets and hyped new business models'' has been cited as a factor that led to the Internet bubble of the late 1990s and its subsequent collapse (Valliere and Peterson, 2004: 10). 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: 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 (H1b): The greater the number of positive vital events in a market, the more likely an organization in that market is to receive venture capital financing.

Entry Selection and the "Non-consensus Entrepreneur"

Entry into a market can be understood as a selection process (Barnett, Swanson, and Sorenson, 2003), such 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, showing that 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, Swanson, and Sorenson, 2003; Nanda and Rhodes-Kropf, 2013).[4] In the first stage of our model, both entrepreneurs and VCs follow vital events into markets. In the second stage, consensus entry results in hazardous long-term effects, because a consensus view that a market has high potential effectively lowers the selection threshold for market entry. We study three outcomes: market exit, receiving VC funding, and going public.

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—which 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 explained, "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 described 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.

In deciding whether to enter a market, entrepreneurs consider both the prospects of the market and how well they can compete in it. Overweighing market potential leads entrepreneurs to underemphasize product–market fit. This means that 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.

[4] Nanda and Rhodes-Kropf (2013) argued 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.

On the flip side, firms in stigmatized markets are heavily scrutinized. An entrepreneur turned investor explained 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 described 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

Our arguments imply that consensus entry results in higher rates of market exit. Positive events lead to a consensus that the market is especially viable, and executives overlook potential issues of fit in the market, which translates into a lower 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 perception that the market is not viable. 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, so only firms very well suited for the market will enter.[5] Thus the non-consensus entrepreneurs on average will be more viable in the market:

> **Hypothesis 2 (H2):** Organizations that enter a market following positive (or negative) vital events will be more (or less) likely to exit that market over time.

[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 in the organization.

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 in 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, as 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 (Carroll and Hannan, 1989; Swaminathan, 1996; Barnett, Swanson, and Sorenson, 2003). 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 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 in which vital events trigger peaks and troughs of entries, and entrepreneurs are least viable when entry is most common, a pattern 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" (Marks, 1993). This view is in tension with the dynamic described above that sees 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 those markets, not the ones that followed the consensus, which are likely to have poor market fit. Consequently:

> **Hypothesis 3 (H3):** Entering markets following positive vital events will reduce an organization's likelihood of receiving venture capital funding.

As Yogi Berra said, "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 (H1b), so VCs will 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 over-supply of funded organizations, with more well-financed competitors than is warranted for future demand. As one VC described it:

> [There are investors who] say, we just really like this space, and I'm not sure they've really thought about the space.[6] 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 someplace 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 (H4):** Organizations that receive venture capital funding during a flood (or drought) of investments are less (or more) likely to later go public.

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, as they help people evaluate complex products that are difficult to understand (Pollock and Williams, 2009; Wang, 2009; Pollock and Williams, 2011). Market categories are typically based on function or product use, and 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) concluded that setting market boundaries is crucial to entrepreneurial success. Market definition is a core part of entrepreneurial strategy.

[6] In the software industry, market categories are referred to as ''market spaces.''

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 in many domains, software categories are subject to trends (Wang, 2010). The faddish nature of this domain led Gartner, the leading information technology analyst, to create a "hype cycle" report that charts a market through what it defines as a cycle that includes "inflated expectations" and a "trough of disillusionment."[7] To stay current, market actors must keep track of which categories are hot and which have become passé.

Venture capital 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 venture capital 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, Sensoy, and Strömberg (2009) argued 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, and Lernout & Hauspie are cautionary tales. The success of a company depends heavily on whether it can dominate a market. As one VC said, 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 make this a good context in which to study long-term effects of consensus and non-consensus market entry.

METHOD

Data

To test the hypotheses, we assembled data on software organizations, the market categories they are in, when they receive VC funding, and when they have an IPO. Our final data set contains 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," gathered from *PR Newswire, Business Wire*, and *ComputerWire*.[8] We used a

[7] http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp (accessed June 21, 2016).

[8] Press releases are available in electronic format starting in 1985. We found that coverage of software companies became comprehensive by 1990. We used press releases from 1989 to construct lagged variables.

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.[9] Press releases are an important medium for software companies to convey news and create public profiles and 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, a software organization identifies the market categories it is in, typically in an ''about'' section at the end. For example, a 1999 press release from Accrue Software referred to it as ''a leading provider of e-business analysis software and services. . . .'' We extracted every identity statement for every software organization in our data 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 its Magic Quadrant reports, and *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 compiled a list of market categories covered in articles from industry publications *Software Magazine* and *Computerworld* and then read through firms' identity statements for additional categories, so 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, and previous research indicates that self-claimed categories are relevant. For example, self-reported markets from 10K statements have been found to better predict financial outcomes than SIC or NAICS codes (Hoberg and Phillips, 2010; Hoberg and Phillips, 2016). Research using press releases has found self-reported markets to predict receiving venture capital financing (Pontikes, 2012) and media coverage (Kennedy, 2008). Markets from press releases 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 used a sample of organizations to investigate whether categorization in press releases reflected the firm's public presentation. We found that market affiliations in press releases were consistent with claims on their websites (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 are on all software organizations. To study entrepreneurs, we included only firms in their start-up phase, meaning we analyzed only young companies in their pre-IPO phase. We excluded all public organizations from our analysis. We gathered IPO information for each software organization using data from Thomson Financial and data maintained by Jay Ritter.[10] To exclude old, private organizations no longer in their entrepreneurial phase, we profiled

[9] 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.

[10] http://bear.warrington.ufl.edu/ritter/ipodata.htm.

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.[11] We excluded 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.[12] To compute firm age, we searched for founding dates in the press releases and from *Hoovers, BusinessWeek*'s private company information, the company's website, or Wikipedia. We located founding dates for 3,705 of the 4,566 organizations. Firms whose founding dates could not be traced likely were not able to attract funding and faded away with little record (except through press releases). Excluding them would bias our analyses, so for the market entry and exit analysis, we included all private firms 12 years old and younger, as well as those for which founding dates could not be located: 3,387 firms.

To measure positive vital events, we used data on when firms received venture capital financing, which come from the Venture Economics database maintained by Thomson Financial. We included only venture capital deals, searching for VC funding for every software organization in the press release data, and found that 822 private organizations received venture capital funding in one or more years.[13] For negative vital events, we used bankruptcies gathered from Thomson Financial, augmented with organizations coded as "defunct" by Venture Economics.[14] Negative vital events are relatively rare—only 68 in these data. A market category exit without bankruptcy may also be considered a failure, so we report the effects of market exits as well in our hypothesis tests.

We augmented these data to construct control variables. We used 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 identified firms that patent using data from the U.S. patent office, maintained by the National Bureau of Economic Research (NBER) (Hall, Jaffe, and Trajtenberg, 2001).[15] We also tracked 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 allowed 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 constructed 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 allowed 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

[11] http://bear.warrington.ufl.edu/ritter/IPOStatistics.pdf.
[12] Firms that are acquired drop out of the data.
[13] Funding histories are limited to after any press release was issued.
[14] In the interest of parsimony, hereafter we refer to all negative events as bankruptcies.
[15] NBER patent data are available through 2006.

releases. When an organization enters the target market, an event occurs, and the dyad is removed from the risk set.[16] We included only 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 estimated the hazard of market entry as:

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

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. Per hypothesis 1a, we expected to find $\alpha < 0$ and $\beta > 0$.

In calculating F_k and V_k, we accounted for the fact that some organizations are in multiple market categories. We weighted each bankruptcy or funding event by the organization's grade of membership in the market, 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. For all our models, we calculated measures of F_k and V_k using grade-of-membership weights.

Hypothesis 2 proposed that an organization's exit from a market category will depend on whether the organization entered in the wake of positive or negative vital events. We created a risk set for each year, including dyads of all entrepreneurial firms and their market categories. An exit is defined as the last consecutive year the organization is in the market category since entry.[17] We studied market exit only, and organizations that exit the data altogether are censored observations. 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:

$$r_{h:Ak}(\tau) = r_{h:Ak}(\tau)^* \times \exp[\gamma_\tau F_{k,\tau=1} + \delta_\tau V_{k,\tau=1}],$$

where $r_{h:Ak}$ is the exit rate of organization A from market k, varying over τ, the duration that organization A has been in market k, and $r_{h:Ak}(\tau)^*$ 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

[16] For organizations that move into and out of categories, only the first entry is counted as an event. We did 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.

[17] Some organizations move into and out of categories. Because we were interested in effects of entry conditions, we defined exit as the first observed exit, and thereafter the dyad was removed from the risk set.

market k at the time of organization A's entry into the category ($\tau = 1$). We allowed estimates of the effects of $F_{k,\tau=1}$ and $V_{k,\tau=1}$ to vary over time τ, to test our argument that the enduring effects of entry conditions take time to materialize. According to hypothesis 2, we expected to find $\gamma_\tau < 0$ and $\delta_\tau > 0$.

In both the entry and exit models, we included a number of controls. Market covariates include the *number of organizations in the market category, entries* into, and *exits* from the market, weighted by grade of membership and logged as they exhibit skew. We included the *leniency* of the market category to control for boundary porousness (Pontikes and Barnett, 2015).[18] We also included the *age of the market*, measured since the inception of our data. Organizational covariates include the *number of markets the organization is in* (logged), 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*.[19] Year dummies are included in all models.

There is a concern in dyadic models about interdependence between observations because actors appear in multiple dyads. We addressed this in two ways. For firm autocorrelation, we included 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 ran models that include dummy variables for each market category (Mizruchi, 1989).

We specified duration using a piecewise exponential model and obtained 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.[20] In all models, independent and control variables are lagged by one year.

VC funding and IPO. To test hypotheses 1b, 3, and 4, we estimated models 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 restricted the risk set by age to exclude old, private organizations that are neither seeking funding nor interested in going public. For the VC analysis, we included organizations less than 15 years old, and for the IPO analysis we included those 20 years and younger (or for which the founding date is not known). We chose age thresholds based on when the data show a substantial drop-off in number of VC funding events or IPOs.[21] 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 excluded firms that enter the press release data the year they go public, because we did not have funding histories of these firms. The risk set for the IPO estimation includes 3,633 organizations over 11,805 organization-years with 356 IPO events.

[18] This is computed using contrast, or the average grade of membership of organizations in the market. $Leniency = (1 - contrast) \times \ln(N_{ocat})$, where N_{ocat} is the number of overlapping categories.

[19] The time since last category entry/exit was measured for the organization and is not equivalent to the hazard clock, which was measured for the dyad.

[20] In models in which category dummies are included, standard errors are clustered by firm.

[21] Results are not sensitive to the age threshold.

The model of the instantaneous rate of VC funding is:

$$r_{vj}(\theta) = r_{vj}(\theta)^{*} \times \exp\left[\in V_j + \zeta C_j\right],$$

where $r_{vj}(\theta)$is the rate of VC funding of organization j, varying as a function of duration since last funding (θ), 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 expected to find $\in > 0$, that an organization's chance of receiving VC funding is increased by being in a category that has recently received funding. We estimated models that include V_k using a quadratic and a piecewise specification, to allow for nonlinearities in the functional form of this effect.

We tested hypothesis 3 using C_j, which measures whether organization j follows VC funding in its market entry. We constructed 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.[22] We took the natural log to reduce skew. Hypothesis 3 predicts that $\zeta < 0$.

We also included controls. The *fuzziness of the organization's markets* (1 – contrast) has been shown to affect evaluations (Kovács and Hannan, 2010; Negro, Hannan, and Rao, 2010; Pontikes, 2012).[23] We included the *number of organizations in the focal organization's markets*, weighted by grade of membership, to control for market competition. We included the *organization's tenure* since inception in the data, its *number of patents, number of acquisitions*, and *whether the organization was ranked in the Software 500 firms* to account for differences in size, resources, and quality. We also controlled 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 α, and $r_{pj}(\alpha)^{*}$ is the baseline rate as a function of controls.[24] 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 calculated V_{kf} in two ways.[25] 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 markets*, weighted by grade of membership, to control for

[22] We also estimated models using different thresholds for VC funding events, as well as a one-year window.

[23] We used fuzziness instead of leniency because it is more predictive in funding models. Results in all models are robust to including leniency.

[24] In models of funded firms only, the clock begins at first funding.

[25] The number of fundings is weighted by the funded organization's grade of membership in the market category. For organizations in multiple categories, we averaged over its categories, weighted by the organization's grade of membership.

market competition, and *the number of markets the organization is in*, to account for generalism. We controlled for whether the *organization previously received venture capital funding, number of funding rounds*, whether it has *patented*, and if it was *ranked in the Software 500* in the previous year, to control for size and quality.[26]

We specified 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 reenters the risk set as a new observation. Therefore we clustered 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. We provide correlations in the Online Appendix (http://asq.sagepub.com/supplemental). Table 2 reports the market entry estimates, including effects for independent variables and select controls.[27] Column 1 is a baseline for comparison. Column 2

Table 1. Descriptive Statistics for Market Category Entry Analysis*

Variable	Mean	S.D.	Min.	Max.
Organization enters market category	.0019	.0431	0	1
VC fundings in market (weighted; logged)	.2571	.4439	0	3.261
Bankruptcies in market (weighted)	.0152	.1095	0	1.667
No. members of market (weighted; logged)	1.155	.9723	0	5.105
No. entries into market (weighted; logged)	.7769	.7878	0	4.474
No. exits from market (weighted; logged)	.7020	.7815	0	4.642
Leniency of market	1.410	.9927	0	4.063
No. Software 500-ranked orgs in market (weighted; logged)	.3594	.5298	0	3.489
No. patenting orgs in market (weighted; logged)	.3297	.4985	0	3.184
Technical proximity of organization to market	.0008	.0176	0	2.447
No. organization's patents (prev. year; logged)	.0675	.2949	0	3.091
Autoregression control	.0019	.0034	0	.0320
Year	1999	2.580	1990	2002

* All independent variables are lagged; (prev. year) is specified in some instances for clarity.

[26] Different controls are included in the VC and IPO models based on theoretical relevance and if they had a significant effect at the $p < .05$ threshold. Significant controls were not excluded, and reported effects are similar when all controls are included.

[27] 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, organization tenure (since 1990), duration pieces for 0–1, 1–2, 2–4, and 4+ years, and year dummies.

Table 2. Models of the Market Category Entry Rate by Software Firms (age $\leq$ 12; private)*

Variable	(1)	(2)	(3)	(4)	(5)
VC fundings in market (weighted; logged)		.250•••	.225•••		.167•••
		(.0657)	(.0667)		(.0431)
$<$ 2 VC fundings in market				.259•••	
				(.0633)	
(2–15) VC fundings in market				.457•••	
				(.0893)	
15+ VC fundings in market				.763•••	
				(.183)	
Bankruptcies in market (weighted)			.143		.0851
			(.0847)		(.0552)
Select controls					
No. members of market (weighted; logged)	.289••	.331•••	.331•••	.269••	.132
	(.104)	(.0964)	(.0936)	(.0970)	(.0698)
No. entries into market (weighted; logged)	.892•••	.745•••	.750•••	.806•••	.400•••
	(.112)	(.104)	(.105)	(.103)	(.0591)
No. exits from market (weighted; logged)	–.227•	–.290••		–.243••	
	(.0981)	(.0939)		(.0880)	
No. exits from market (excl. bankrupt)			–.294••		–.279•••
			(.0941)		(.0467)
Leniency of market	.407•••	.399•••	.402•••	.374•••	.0655•
	(.0349)	(.0329)	(.0330)	(.0366)	(.0316)
Autoregression control	100.2•••	100.4•••	100.4•••	100.3•••	100.7•••
	(2.087)	(2.084)	(2.083)	(2.078)	(2.373)
Category dummies	No	No	No	No	Yes
Log pseudo-likelihood	–33,615.0	–33,584.8	–33,581.6	–33,576.3	–32,723.8
Degrees of freedom	27	28	29	30	473

• $p < .05$; ••$p < .01$; •••$p < .001$.
* Standard errors are in parentheses.

includes a category's venture capital fundings in the previous year, to test hypothesis 1a. The effect is positive and significant at $p < .001$. 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 $p < .10$. Results provide support for hypothesis 1a in terms of positive vital events: organizations enter markets following VC investment.

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 $p < .001$, indicating that heterogeneity among categories is not driving the result. The bankruptcy effect is not significant when category fixed effects are included. 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, consistent with a pattern in which 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

Table 3. Models of the Market Category Entry Rate by Software Firms (age ≤ 12; private)*

Variable	(1) 1-year spells	(2) 6-month spells	(3) 1-year spells	(4) 1-year spells
VC fundings in market, prev. period (weighted; logged)	.221••	.156••	.227•••	
	(.0709)	(.0525)	(.0645)	
VC fundings in market, 2 periods prior (weighted; logged)	.0610	.0564		
	(.0499)	(.0539)		
Fundings in market: all other VCs (weighted; logged)				.244•••
				(.0646)
Fundings in market: low-status VCs (weighted; logged)				.0353
				(.0975)
Select controls				
No. members of market (weighted; logged)	.323••	.514•••	.255•	.335•••
	(.0989)	(.0576)	(.102)	(.0984)
No. entries into market (weighted; logged)	.757•••	.517•••	.732•••	.745•••
	(.109)	(.0648)	(.103)	(.105)
No. exits from market (weighted; logged)	–.308••	–.131••	–.305••	–.289••
	(.0939)	(.0464)	(.0961)	(.0921)
Leniency of market	.398•••	.444•••	.400•••	.400•••
	(.0326)	(.0307)	(.0344)	(.0330)
Autoregression control	100.4•••	147.9•••	100.2•••	100.3•••
	(2.082)	(2.315)	(2.083)	(2.081)
No. Software 500-ranked orgs. in market (weighted; logged)			.0619	
			(.0551)	
No. patenting orgs. in market (weighted; logged)			.128•	
			(.0634)	
Technical proximity of organization to market			.628••	
			(.238)	
No. organization's patents (prev. year; logged)			.00274	
			(.0397)	
Log pseudo-likelihood	–33,583.0	–38,656.6	–33,568.0	–33,585.1
Degrees of freedom	29	42	32	29

• $p < .05$; ••$p < .01$; •••$p < .001$.

* Standard errors are in parentheses. All independent variables are lagged; (prev. year) is specified in some instances for clarity.

and competition within a market (Hannan and Freeman, 1989). 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.[28]

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 expected 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 explored the effect of recent vital events by running a model that uses

[28] 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.

six-month spells (column 2).[29] Results show that positive vital events in the most recent period have a positive effect on entry.[30]

Column 3 in table 3 includes controls that test against a number of alternatives. We investigated 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 in which there is strong demand. We cannot reject the null hypothesis 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 included 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 expected 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 tested 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, we conducted an exploratory analysis. Column 4 in table 3 presents estimates that separate vital events based on the status of the VC investment firm. We measured 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 separated the VC funding variable into pieces based on whether the VC firms investing in the market were low-status firms according to this index.[31] 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 $p < .12$). This suggests that 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 Online Appendix).

[29] For some press releases (1.5 percent), 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.

[30] 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).

[31] We coded 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, and 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 found that investment by excluded firms has a similar effect to those ranked above 150. As a result we pooled these in the "all other VC" variable.

Table 4. Descriptive Statistics for Venture Capital Funding Analysis*

Variable	Mean	S.D.	Min.	Max.
Org. receives VC funding	.1449	.3520	0	1
No. categories entered after 2+ VC fundings (2-year window; logged)	.1094	.3099	0	2.398
No. categories entered and exited in the previous year	.3922	.9090	0	11
VC fundings in market (prev. year)	2.782	3.935	0	25.07
Fuzziness of organization's markets	.3633	.2760	0	.8332
No. members of organization's markets (weighted; logged)	2.296	1.922	0	6.549
Org.'s tenure in data	1.742	1.956	0	13
No. organization's patents (prev. year)	.1641	.9623	0	21
No. acquisitions (prev. year)	.0077	.0946	0	4
No. previous VC funding rounds	.6412	1.653	0	20
Organization ranked in Software 500 (prev. year)	.0581	.2339	0	1
Year	1998	2.968	1990	2002

*All independent variables are lagged; (prev. year) is specified in some instances for clarity.

Table 5 reports results.[32] 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: positive and increasing up until 15 fundings ($p < .10$ for < 2 VC fundings), and thereafter falling to become negative and nonsignificant. This provides support for hypothesis 1b for most of the observed range of funding.

Columns 4 and 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 by two-thirds 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.

Results are similar in magnitude if we use a one-year window ($p < .15$) or if we do not take the natural log ($p < .05$). But 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 tested whether this effect is a result of organizations that engage in market search. Column 5 in table 5 includes a control for the number of

[32] All models include duration pieces for 0–1 year, 1–3 years, 3–5 years, and 5+ years, and year dummies.

Table 5. Models of the VC Funding Rate for Software Organizations*

Variable	(1)	(2)	(3)	(4)	(5)
No. categories entered after 2+ VC fundings (2-year window; logged)				–.261•	–.251•
				(.107)	(.110)
No. categories entered and exited in the previous year					–.0173
					(.0299)
VC fundings in market (prev. year)		.0412•			
		(.0182)			
VC fundings in market (prev. year) sq.		–.0028••			
		(.0011)			
< 2 VC fundings in market			.200	.194	.192
			(.107)	(.107)	(.107)
(2–15) VC fundings in market			.286••	.279•	.275•
			(.111)	(.111)	(.111)
15+ VC fundings in market			–.0597	–.0760	–.0829
			(.190)	(.189)	(.189)
Fuzziness of organization's markets	1.346•••	1.357•••	1.323•••	1.180•••	1.179•••
	(.224)	(.226)	(.227)	(.234)	(.234)
No. members of organization's markets (weighted; logged)	.0534	.0456	.0461	.0715•	.0772•
	(.0292)	(.0294)	(.0294)	(.0318)	(.0324)
Org.'s tenure in data	–.0666•	–.0642•	–.0638•	–.0449	–.0479
	(.0282)	(.0285)	(.0283)	(.0284)	(.0292)
No. organization's patents (prev. year)	.0151	.0158	.0162	.0151	.0145
	(.0230)	(.0227)	(.0230)	(.0228)	(.0229)
No. acquisitions (prev. year)	.0305	.0304	.0298	.0384	.0502
	(.296)	(.297)	(.295)	(.305)	(.309)
No. previous VC funding rounds	.165•••	.166•••	.167•••	.169•••	.169•••
	(.0278)	(.0275)	(.0275)	(.0262)	(.0262)
Organization ranked in Software 500 (prev. year)	–.163	–.175	–.179	–.174	–.171
	(.158)	(.158)	(.158)	(.158)	(.156)
Log pseudo-likelihood	–3979.5	–3975.8	–3974.0	–3970.2	–3970.0
Degrees of freedom	23	25	26	27	28

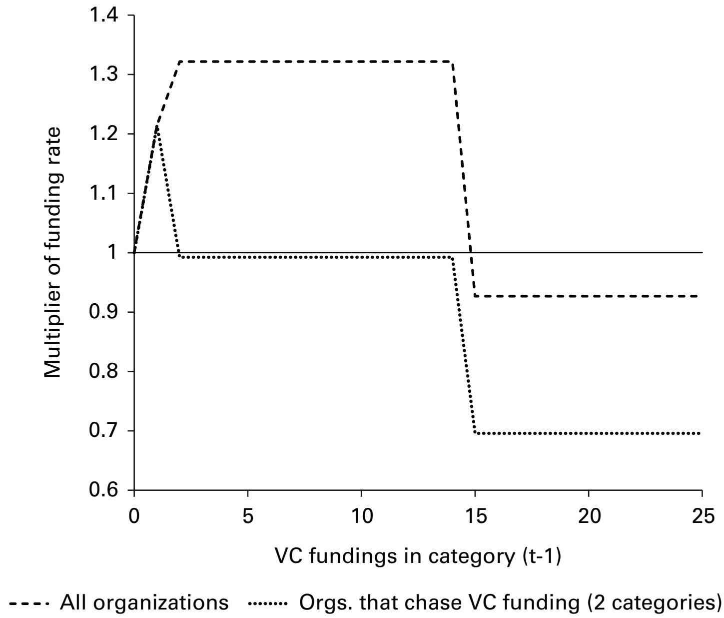
• $p < .05$; ••$p < .01$; •••$p < .001$.

* Standard errors are in parentheses. All independent variables are lagged; (prev. year) is specified in some instances for clarity.

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). 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.

Figure 1. Predicted effects of VC funding for all organizations and organizations that chase funding.*



* Based on results from table 5, column 4.

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, including independent variables and select controls.[33] 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 measured 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.

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 collapsed 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

[33] 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, and year dummies.

Table 6. Descriptive Statistics for Market Category Exit Analysis

Variable	Mean	S.D.	Min.	Max.
Organization exits category	.3284	.4696	0	1
VC fundings in market at time of entry (weighted; logged)	.7625	.8290	0	3.261
Bankruptcies in market at time of entry (weighted)	.0431	.1844	0	1.107
No. members of market (weighted; logged)	2.468	1.258	0	5.105
No. entries into market (weighted; logged)	1.912	1.173	0	4.474
No. exits from market (weighted; logged)	1.634	1.178	0	4.397
Autoregression control	.3062	.3841	0	1
Year	1998	2.733	1990	2001

Table 7. Models of the Market Category Exit Rate by Software Firms (age $\leq$ 12; private)*

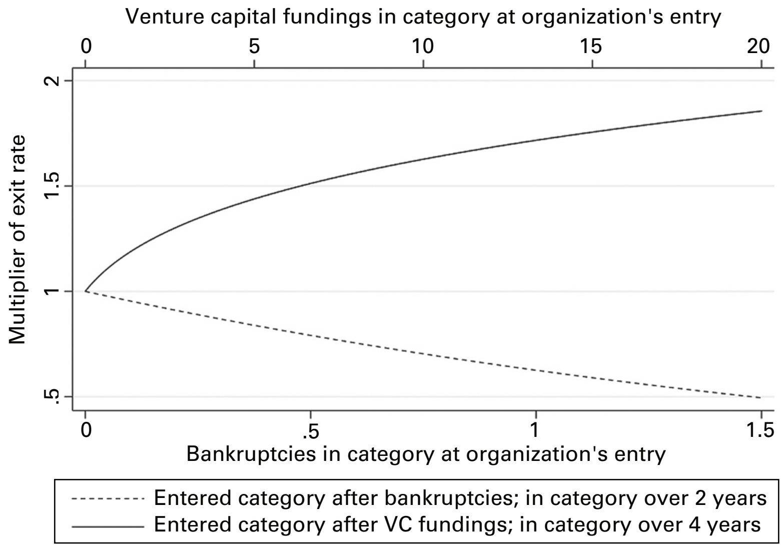
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Bankruptcies in market at entry:						
Duration (0–2) years	−.0298	−.00262	−.0455	−.0344	−.00308	−.0496
	(.0744)	(.0738)	(.0759)	(.0767)	(.0733)	(.0785)
Duration (2–4) years	−.556	−.587	−.557•	–	–	–
	(.298)	(.367)	(.258)	–	–	–
Duration 2 + years	–	–	–	−.469•	−.536	−.455•
	–	–	–	(.203)	(.306)	(.197)
Duration 4 + years	−.236	−.297	−.0736	–	–	–
	(.262)	(.756)	(.189)	–	–	–
VC fundings in market at entry:	*Prev. year*	*Prev. year*	*Prev. 6 months*	*Prev. year*	*Prev. year*	*Prev. 6 months*
Duration (0–2) years	−.0418	−.00916	−.0287	–	–	–
	(.0371)	(.0343)	(.0404)	–	–	–
Duration (0–4) years	–	–	–	−.0398	−.0091	−.0267
	–	–	–	(.0361)	(.0341)	(.0395)
Duration (2–4) years	−.00751	−.00381	.0139	–	–	–
	(.0815)	(.0663)	(.0934)	–	–	–
Duration 4 + years	.192	.178	.225•	.203	.190	.237•
	(.122)	(.122)	(.0955)	(.115)	(.115)	(.0926)
Select controls						
No. members of market (weighted; logged)	−.105	.413•••	−.106	−.106	.413•••	−.108
	(.0570)	(.0675)	(.0564)	(.0567)	(.0674)	(.0560)
No. entries into market (weighted; logged)	−.117•	−.251•••	−.122••	−.117•	−.250•••	−.121••
	(.0485)	(.0534)	(.0472)	(.0484)	(.0533)	(.0471)
No. exits from market (weighted; logged)	.227•••	−.0358	.224•••	.229•••	−.0357	.226•••
	(.0556)	(.0445)	(.0546)	(.0552)	(.0444)	(.0540)
Autoregression control	1.208•••	1.231•••	1.208•••	1.208•••	1.231•••	1.208•••
	(.0336)	(.0375)	(.0336)	(.0335)	(.0375)	(.0335)
Category dummies	No	Yes	No	No	Yes	No
Log pseudo-likelihood	−12,219.1	−11,914.1	−12,219.6	−12,219.3	−11,914.1	−12,219.9
Degrees of freedom	32	440	32	30	438	30

• $p < .05$; ••$p < .01$; •••$p < .001$.

* Standard errors are in parentheses.

after two years in the category, significant at $p < .05$. Those that enter after VC fundings are more likely to exit after four years ($p < .08$). Results are consistent in column 6, which uses entry after VC fundings in the previous six

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.

months ($p < .05$). Effects are also similar when category fixed effects are included in column 5 ($p < .10$), suggesting that differences between categories do 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.

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 the 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.[34] Column 2 reports an estimate that

[34] All models include duration pieces for 0–1 year, 1–3 years, 3–5 years, 5–7 years, and 7+ years, and year dummies.

Table 8. Descriptive Statistics for IPO Analysis*

Variable	Mean	S.D.	Min.	Max.
Organization goes public (IPO)	.0302	.1710	0	1
VC fundings in market(s) at round 1 funding	.2342	1.464	0	25.07
VC fundings in market(s) at round 1 funding (logged)	.0765	.3554	0	3.261
VC fundings in market(s), average over all fundings	.5450	2.034	0	25.07
No. members of organization’s markets (weighted; logged)	2.397	1.899	0	6.549
No. markets organization is in (logged)	.7462	.5969	0	2.890
Received VC funding	.1340	.3407	0	1
Number of funding rounds	.6110	1.646	0	20
Organization has patented	.1249	.3307	0	1
Organization ranked in Software 500 (prev. year)	.0717	.2579	0	1
Year	1998	2.930	1990	2002

* All independent variables are lagged.

Table 9. Models of the IPO Rate by Software Firms*

Variable	(1) All orgs.	(2) All orgs.	(3) All orgs.	(4) Funded	(5) All orgs.	(6) Funded
VC fundings in market(s), average over all fundings		–.0401				
		(.0437)				
VC fundings in market(s) at round 1 funding			–.0898	–.131$^{\bullet}$		
			(.0533)	(.0584)		
VC fundings in market(s) at round 1 funding (logged)					–.185	–.335$^{\bullet}$
					(.151)	(.161)
No. members of organization’s markets (weighted; logged)	–.162$^{\bullet\bullet}$	–.145$^{\bullet}$	–.158$^{\bullet}$	–.181	–.160$^{\bullet\bullet}$	–.186
	(.0608)	(.0636)	(.0612)	(.106)	(.0610)	(.105)
No. markets organization is in (logged)	.634$^{\bullet\bullet\bullet}$	.599$^{\bullet\bullet\bullet}$	.613$^{\bullet\bullet\bullet}$	.663$^{\bullet}$	.623$^{\bullet\bullet\bullet}$	.689$^{\bullet}$
	(.171)	(.176)	(.172)	(.286)	(.172)	(.284)
Received VC funding	.857$^{\bullet\bullet\bullet}$	.965$^{\bullet\bullet\bullet}$	1.001$^{\bullet\bullet\bullet}$		.988$^{\bullet\bullet\bullet}$	
	(.158)	(.195)	(.177)		(.189)	
Number of funding rounds	.0630$^{\bullet}$	.0604$^{\bullet}$	.0484	.0145	.0496	.0105
	(.0275)	(.0277)	(.0294)	(.0356)	(.0301)	(.0368)
Organization has patented	.712$^{\bullet\bullet\bullet}$	.716$^{\bullet\bullet\bullet}$	.715$^{\bullet\bullet\bullet}$	.652$^{\bullet\bullet\bullet}$	.711$^{\bullet\bullet\bullet}$	.642$^{\bullet\bullet\bullet}$
	(.117)	(.117)	(.117)	(.187)	(.117)	(.188)
Organization ranked in Software 500 (prev. year)	.751$^{\bullet\bullet\bullet}$	.753$^{\bullet\bullet\bullet}$	.784$^{\bullet\bullet\bullet}$	.982$^{\bullet\bullet\bullet}$	.776$^{\bullet\bullet\bullet}$	.977$^{\bullet\bullet\bullet}$
	(.141)	(.141)	(.142)	(.234)	(.143)	(.236)
Log pseudo-likelihood	–924.1	–923.6	–922.4	–307.5	–923.3	–308.3
Degrees of freedom	23	24	24	23	24	23

$^{\bullet}p < .05$; $^{\bullet\bullet}p < .01$; $^{\bullet\bullet\bullet}p < .001$.

* Standard errors are in parentheses. Data for funded firms contain 642 organizations (age $\leq$ 20) that received funding after appearing in the press release data over 1,582 years, with 129 IPO events.

includes the average VC fundings in the organization’s markets across all years it received funding. This effect is nonsignificant. 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 ($p < .10$) for the nontransformed measure and nonsignificant when the logged measure is used. Columns 4 and 6 restrict the risk set to funded organizations. Results show a positive and significant effect ($p < .05$) for both measures, providing 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.

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, and 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.

Additional Analyses

Entrepreneurship in established firms. In recent years, there has been a push toward recognizing entrepreneurship in established companies, especially in high technology. Ries (2011: 25) commented 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." 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 with 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 enter 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. Previous work has suggested that intense competition at founding can lead to long-term hazards, generally attributed to resource scarcity (Carroll and Hannan, 1989; Swaminathan, 1996; cf. Barnett, Swanson, and Sorenson, 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 because they 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 the assessment is the opposite. Because these assessments change the level of scrutiny for organizations entering a market, they shape the average viability of firms that enter a market following positive and negative vital events. The estimates of our models align with our predictions. 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. We also 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 foolish 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, which leads to rapid exit. Thus 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 overcrowded market in which 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 to exit, perhaps looking for the next new fad, and the process starts anew. While 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 and 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 that 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. 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 effects are not significant for those that receive investment following positive events averaged across all funding rounds. Investors that follow others in their first investment exhibit consensus behavior, but those that provide subsequent funding likely invested in the category before the hype. Many of these were initially non-consensus investors who 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 overprioritize market viability, leading them to underemphasize 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 VC Peter Thiel (2014: 22) wrote, "You can't escape the madness of the crowds by dogmatically rejecting them. . . . The most contrarian thing of all is not to oppose the crowd but to think for yourself." It is important for entrepreneurs to scrutinize any move and carefully consider how their firm can compete in a market. Our study indicates that market potential looms large for entrepreneurs and investors, leading many to take shortcuts in estimating how well they can fare 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 their 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.[35]

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 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 the ideal online advertisement-based business. Another iconic example is the Apple Newton, a handheld 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, and social networks. Perceptions of a market's potential (or peril) change rapidly 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 stated, ''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 added, ''[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 its decision to enter a new, more promising area.

Our focus on vital events demonstrates the merit of 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 rethinking 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 firms' behavior.

[35] 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.

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, and 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 underweigh the ability of their firm to serve that market. It is possible that entrepreneurs can 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 is that it is difficult to engage in a sober analysis of product–market fit in the midst of market hype, so additional scrutiny is important. Entrepreneurial teams that are tempted to enter hot markets should wrestle with this question: if the company is so well positioned to dominate that category, why was it 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 has shown that negative signals are stronger than positive ones (Baumeister, Bratslavsky, and Vohs, 2001) and that stigma readily spreads in markets (Jonsson, Greve, and Fujiwara-Greve, 2009; Pontikes, Negro, and Rao, 2010). We do find a negative effect of previous market exits on future entry. Exits also can indicate 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: in one the market becomes stigmatized and so potential entrants stay away, and in the other bankruptcies create excess capacity that can be purchased inexpensively. The combination may lead to the observed effect, where the null hypothesis cannot be rejected. We do find that firms entering a market after bankruptcies are more likely to stay, which 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's (2013), who investigated outcomes for firms funded in hot time periods, when many other firms receive funding. They found 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. These effects are 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, Swanson, and Sorenson, 2003) but does not explain why density is high at a given time. Our research design allowed us to study both topics. We 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, in which 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 we directly measure vital events that create consensus. 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 13 years.

In our model, positive vital events lead to increases in density at entry because perceptions of munificence lower the entry threshold, resulting in a flood of new entrants. 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 to indicate only competition. Our measure of positive vital events is a less ambiguous signal. It may be interesting for future researchers to find a context in which 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 have an 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, non-consensus behavior may be the more sustainable strategy.

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Authors' Biographies

Elizabeth G. Pontikes is an associate professor of organizations and strategy and William S. Fishman scholar at the University of Chicago Booth School of Business, 5807 S Woodlawn Ave., Chicago, IL 60613 (e-mail: elizabeth.pontikes@chicagobooth.edu). She studies market categorization, innovation, and stigma. She received her Ph.D. in Business Administration from the Stanford Graduate School of Business in organizational behavior.

William P. Barnett is the Thomas M. Siebel Professor of Business Leadership, Strategy, and Organizations at the Graduate School of Business, Stanford University, Stanford CA 94305. His research looks at systems of competition within and among organizations. Barnett received his Ph.D. in Business Administration from the University of California, Berkeley.