Was there too little entry during the Dot Com Era?*

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Abstract

We present four stylized facts about the Dot Com Era: (1) there was a widespread belief in a "Get Big Fast" business strategy; (2) the increase and decrease in public and private equity investment was most prominent in the internet and information technology sectors; (3) the survival rate of dot com firms is on par or higher than other emerging industries; and (4) firm survival is independent of private equity funding. To connect these findings we offer a herding model that accommodates a divergence between the information and incentives of venture capitalists and their investors. A Get Big Fast belief cascade may have led to overly focused investment in too few internet startups and, as a result, too little entry.

1 Introduction

When the NASDAQ index peaked at 5,132 on March 10, 2000, it stood more than 500% above its level on August 9, 1995, the day of the Netscape IPO. By September 23, 2002, the NASDAQ closed at 1,185. The 18-month decline of stock prices resulted in $4.4 trillion of market value loss—including $1 trillion in Silicon Valley's 150 largest companies. It was the largest stock market collapse in the history of industrial capitalism (Cassidy 2002; Mahar 2003).

We present and provide evidence for four stylized facts about business creation during the Dot Com Era (1995–2000). Facts 1, 3, and 4 are novel to the literature.

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1. There was a prevalent belief that a "Get Big Fast" business strategy was appropriate for internet businesses. This strategy fell from favor only after the resolution of uncertainty about its efficacy in early 2000.

2. The rise and fall of VC investment sizes and total investment was most prominent in the internet and other information technology sectors. While overall VC investment fell after the stock market decline in 2000, internet-related VC investments fell more and internet-related IPOs virtually ceased.

3. Exit rates of dot com firms are comparable with or perhaps lower than exit rates of entrants in other industries in their formative years. Five year survival rates of Dot Com firms approach 50%.[1]

4. Survival is unrelated to the receipt or the amount of private equity financing. VC-financed and other privately financed firms were neither more nor less likely to survive. There is no evidence that return on private equity investment was positive or that, conditional on survival, internet traffic ratings was higher for private equity-backed firms.

To interpret these facts, we examine beliefs of private equity investors whose investment targets were sold on the IPO market. We find that the private equity market and also the public markets were fed by investors' pursuit of a "Get Big Fast" (GBF) entry strategy (Fact 1). This strategy, based on preemption and economies of scale loosely associated with network effects, became prevalent in the venture capital community. At the time, there was scant direct evidence supporting the broad application of the strategy for internet businesses. Drawing on the herding literature, we develop a model that explains the emergence of a GBF belief cascade. The model identifies theoretical conditions that increase the likelihood of belief cascade formation and persistence. First, decision-makers lack information about the viability of particular entry strategies; second, the arrival of such information is sufficiently delayed to allow a cascade to form. These conditions are consistent with Fact 1.

Fact 2 suggests that the market for internet-related investments soured once it became clear that many firms started under the GBF strategy were failing. If GBF was indeed the problem, then one might expect VCs to have switched to more promising strategies, correcting their earlier errors rather than ceasing their investment activity. Our theory

[1] This survival rate is lower than manufacturing industries, in which approximately 2/3 of entering manufacturers survive five years (Agarwal and Audretsch 2001; Dunne, Roberts, and Samuelson 1988), but matches or exceeds survival rates in initial shakeouts of other emerging industries (Simons 1995), a more appropriate benchmark. This fact was first reported in Goldfarb, Kirsch, and Pfarrer (2005) for a slightly larger sample that included firms that did not list any internet-revenue models. The survival rate is identical when excluding these firms.

explains how the market can crash rather than correct, even when VCs learn that a non-GBF strategy is preferable. The theory accommodates both venture capitalists' beliefs and the beliefs of the less-informed investors who supply capital to the VCs. The information asymmetry, together with the limited liability of the VCs, generates VC investment behavior inconsistent with that desired by investors. In particular, once the GBF belief cascade ends, investors may cut off funding for VC investments because they worry that VCs are investing too aggressively rather than switching to a more appropriate investment strategy. This leads to a crash rather than a correction. The behavior of investors in the model is metaphorically interpreted to reflect that of both IPO market investors and limited partners in VC funds. Incorporating different layers of beliefs between multiple types of decision makers generates rich investment dynamics broadly consistent with Fact 2 while also advancing the herding literature.

The pervasive and persistent belief in the GBF strategy may have dissuaded entry at the margin. If for most potential entrants this strategy was not profit maximizing, then many decisions not to enter were based upon false assumptions. This reasoning suggests that too few firms were formed to commercialize the internet and is the basis of our Too-Little-Entry hypothesis. Too little entry would lead to high survival rates for those firms that did enter (Fact 3).

Finally, if GBF was generally ill-advised, then one might expect pursuit of this strategy to be associated with firm failure. However, there are three counteracting effects. First, GBF necessarily required the receipt of large amounts of capital, generally through private equity investments; both capital resources and the expertise associated with private capital are thought to enhance the likelihood of successful firm outcomes. Second, a first entrant using the GBF strategy will discourage other potential entrants if they also believe that GBF is the correct strategy, helping the first entrant avoid competition. Third, if the market for internet-related investments undergoes a crash rather than a correction, funding will not be available for later, smaller entrants, increasing the likelihood that the first entrant will succeed even if GBF is the wrong strategy non-profit-maximizing strategy. If the error in business strategy choice was sufficiently detrimental to overcome these effects, we should observe a negative or non-positive relationship between private equity investment and firm survival. Fact 4 is consistent with a detrimental effect of GBF.

While we believe that our theory best explains events in the private equity and entrepreneurial markets, our empirical results are, generally, consistent with and complementary to the conclusions of existing scholarship. For example, research on the Dot Com Era documents public market movements (Ofek and Richardson 2002) and generally concludes that these movements were driven by over-optimism and event-driven irrationality (Bitmead, Durand, and Ng 2004; Cooper, Dimitrov, and Rau 2001; Lamont and Thaler 2003;

Ofek and Richardson 2003). Cooper et al. (2001) show evidence that changing the name of a company to include "dot com" led to stock price increases. Lamont and Thaler (2003) examine carve-outs and find evidence of exuberant pursuit of technology stocks even when they could have been purchased less expensively by purchasing stock of their parent firms. Bitmead et al. (2004) find evidence of irrational behavior in their analysis of auto-correlation of daily internet stock movements before and after the stock market decline of beginning in March 2000. Ofek and Richardson (2003) link the bursting of the bubble to the expiration of insider's lock-up agreements, suggesting that uninformed market participants drove the overvaluation of internet stocks. To the extent that public market participants believed they were investing in companies pursuing the GBF strategy, Fact 1 is consistent with these theories.

The emergence of a belief cascade is also consistent with arguments made by Pástor and Veronesi (2005), who question the existence of irrational beliefs and suggest that NASDAQ stock prices reflected high levels of uncertainty about the viability of particular businesses. We argue that the belief cascade was able to propagate because it was unknowable whether the GBF strategy was generally viable until early 2000. In this respect, the spirit of our analysis (although not the context) is perhaps closest to Persons and Warther (1997). In Persons and Warther's model of financial innovation adoption, the benefit of adoption varies from firm to firm. High expected benefit firms adopt first. This provides to others a noisy signal of the benefits of adoption. Each time an (average) high-benefit signal is realized, more marginal firms adopt. More firms adopt with each successive signal due to the reduction of uncertainty—signals aggregated from many firms are more reliable than those from just a few. Eventually, a sufficiently negative (average) draw may stop the process. When that happens, and with the benefit of hindsight, the later adopters who experienced negative results may appear foolish. However, given the information these laggards had at the time of their decisions, their behavior was rational. Our model differs in that we allow two types of decision makers (VCs and investors). This generates a mechanism to escape the bust cycle, a feature that the Persons and Warther's model lacks.

In our context, these theories are best interpreted in light of the literature that describes a strong link between the performance of the IPO and venture capital markets (Black and Gilson 1998; Gompers and Lerner 2001; Gompers, Lerner, Blair, and Hellman 1998; Inderst and Muller 2004; Michelacci and Suarez 2004; Stuart and Sorenson 2003). This is often referred to as the "recycling" mechanism: investment funds are recycled in the sense that IPO market proceeds are reinvested in new startups. Strong public market performance is predicted to lead to an increase in valuations. If VCs wish to maintain a constant ownership share, rising valuations would increase the size of individual investments and also lead to an increase in VC fundraising (Fact 2). Our finding of a cascade (Fact 1) articulates one specific way in which the market overreacted to the technological opportunity associated with the internet, as suggested by Inderst and Muller (2004). If the arrival of the internet were interpreted as an increase in the rate of technological progress, Michelacci and Suarez (2004) predict younger companies going public and an increase in startups (Fact 2). However, the literature is silent as to the causes of the gyrations and their concentration in the internet and IT sectors, except insofar as to hypothesize that there may have been a productivity shock associated with the internet.

If irrational behavior in the public markets led to entry into the venture capital market and pursuit of increasingly marginal opportunities, we should see poor long-term performance of firms responding to the pull of the public market. This prediction is consistent with Fact 4. However, both the Dot Com literature and the recycling literature would predict poor survival outcomes of internet related ventures. This prediction is not consistent with Fact 3.

More generally, VCs select the highest quality ventures from the overall pool of solicitations they receive. They are also presumed to enhance the prospects of their ventures through monitoring and intervening in decision making (cf. Gompers and Lerner 2000). To the extent that VCs and other private equity investors select better businesses and add value to new enterprises, their involvement should have a positive effect on firm survival. Therefore, there are strong reasons to expect a positive correlation between the magnitude of private equity investments and survival. Moreover, recent work on industry evolution relates survival in new industries to entry size by assuming that more productive firms enter at larger scale (Buenstorf and Klepper 2005; Klepper 2002). Fact 4 is inconsistent with both these predictions. Fact 4 is also surprising given an established general empirical relationship between entry size and survival (Agarwal and Audretsch 2001; Dunne et al. 1988; Mata and Portugal 1994).

Finally, our predictions run counter to the conventional wisdom about the pervasive failure of internet firms following the decline of the stock market in 2000–2002. This belief has been echoed, or perhaps propagated, by anecdotal media accounts describing these events (cf. Cassidy 2002; Lowenstein 2004). By systematically examining the outcomes of a representative sample of firms, as in Goldfarb et al. (2005), we find that such anecdotal accounts are not representative of the full population.[2] In this respect, our results support Hendershott (2004) who, analyzing the financial performance (as opposed to survival) of a portfolio of over 435 Dot Com VC investment targets, finds that \$1 of VC funds invested in Dot Com firms from 1995-2000 is worth \$1.8 at the end of 2001. While he also finds that these positive returns are almost entirely driven by internet investments in a handful of

[2] We acknowledge the unprecedented paper wealth destruction during the decline of the public markets in 2000–2002. However, we find that this destruction did not arise from systematic closure of internet firms.

companies made in 1995 through 1997, the preponderance of evidence, he suggests, is that the positive returns are not best explained by a first mover advantage in individual markets, but rather by an early identification of the most profitable opportunities.Our analysis also finds that VC investments made in the late 1990s were ill-advised. Moreover, we are able to attribute these errors to a specific belief: the GBF business strategy. However, by analyzing a broader range of startups and looking at survival as opposed to returns, we find Fact 3, which together with Hendershott's results, suggests that while the opportunities pursued after 1997 were inappropriate for the GBF strategy, many were still viable.

In the following pages we document a series of stylized facts and present a broad theory of belief formation during the Dot Com Era. On the whole, our interpretation should be viewed as enhancing rather than refuting current thinking. For example, per the recycling literature, our model assumes a strong link between the public and private equity markets. Our exposition proposes rational decision making, but cannot explain all public market anomalies identified by the literature that argues irrational exuberance. Finally, we do not suggest that, in general, the theories of VC selection and value creation are wrong. However, in our context the mechanisms identified by that literature may have been overwhelmed by a belief cascade.

In the paper, we tie the emergence of the GBF cascade to the popularization of ideas associated with increasing returns to scale and lock-in in the academic literature (e.g., Arthur 1996; Shapiro and Varian 1999).In our paper, we find a general willingness to pursue the GBF strategy (and thereby apply these theories in practice) despite scant information of its efficacy. Our results suggest that this pursuit was a sub-optimal strategy. Moreover, given that it called for large commitments, this misapplication of academic theory had severe financial consequences. In this respect, our findings add color to the literature that traces the impact of academic theories on economic systems (e.g., Faulhaber and Baumol 1988 and others). To be clear, we do not challenge the underlying logic of the academic theories, rather we suggest that they were, in retrospect, misapplied. We refer the reader to Liebowitz (2002) for an in depth argument on why these theories were inappropriate for application to internet businesses.

Our analysis draws upon two datasets: the Venture Economics database as well as a dataset of Dot Com Era startups first introduced in Goldfarb et al. (2005). The latter dataset is comprised of firms that submitted business proposals to a single VC between 1998 and 2002; these firms are tracked through 2004.[3] Goldfarb et al. (2005) show that these data are representative of the broad population of internet startups. Moreover, since the sample is not selected on success events such as VC funding or IPO, it captures significant

[3]The data are a sub-sample of business planning documents preserved at the Business Plan Archive (BPA; http://www.businessplanarchive.org).

variation in the pursuit of the GBF strategy.[4] This characteristic of the data allows us to test the viability of the GBF strategy and in particular measure the marginal effect of each additional investment dollar on hazard rates of exit.

Our paper proceeds as follows. In Section 2 we introduce our theoretical model and with it, identify possible indications of a belief cascade in the historical record of the internet era. In Section 3, we provide evidence that supports the Too-Little-Entry hypothesis and the hypothesis that GBF was an ill-advised strategy for most internet ventures. Section 4 describes the limitations of our analysis, and Section 5 concludes.

2 Theory and History

We divide this section into five parts. First, we summarize the theory, which identifies conditions under which a primary cascade on "Get Big Fast" may form. Second, we provide historical evidence for the kinds of the conditions identified in the model. Third, we return to the model and articulate conditions for generating a subsequent suspension of investment following the realization that GBF was ill-advised. This generates several predictions regarding the patterns of venture capital investments and commitments before and after the fall of the stock market prices beginning in March 2000 that we explore in the fourth part. Finally, we develop the theoretical underpinnings of the Too-Little-Entry hypothesis and the predictions following therefrom.

2.1 Primary Cascade: Theory

The model characterizes conditions under which VCs will invest in startup projects, as well as conditions under which investors will commit funds to the VCs. The theoretical model and a parameterized example are developed formally in the Appendix. Throughout, it is important to recognize that our model is stochastic and can generate many different realizations. The contention of our theory is that important aspects of the Dot Com Era are represented by a certain subset of the realizations that can be generated by our model. We focus on this class of realizations because it displays characteristics similar to those of the historical record, and provides a unified explanation for what occurred.

In the model there are three types of opportunities, "large-scale" entry (L), "small-scale" entry (S), and opportunities that are inappropriate for VCs. The true likelihood of observing an opportunity of a particular type is never known, although the VCs form beliefs about this distribution. Each VC, in turn, evaluates an opportunity and receives a private, noisy signal

[4]Goldfarb et al. (2005) describe the data used in this paper and in addition to reporting survival rates, based on their conclusions of general representativeness, create estimates of the number of firms created to exploit the internet during the period, and detail the amount and distribution of private equity to these firms.

as to its type. If the VC decides that the opportunity cannot provide sufficient returns, it invests in risk-free bonds (B). Alternately, the VC matches its level of investment to its best guess of the opportunity type, thereby creating either a large (L) or small (S) project. The investment is profitable only if the VC has correctly matched the project type to the opportunity type. For example, an investment in a project that relies on a rapid accumulation of market share and a GBF strategy (L in our model) is successful if and only if—in that market—GBF is a profitable strategy.

When an investment is made, all other VCs observe its type. However, investors observe only whether the VC invested in a project or in bonds; that is, investors cannot distinguish L projects from S projects. The profitability of each investment is revealed at two dates. T_1 periods after the investment, the entire population of VCs observes the project's profitability. Each project takes T_2 periods to mature, at which time its profits are realized and become observable to the investors. VCs receive a percentage of profits as compensation. There are three key elements of the model that generate the results: (i) the asymmetric information among VCs, which makes them unable to view each others' signals; (ii) the asymmetric information between VCs and investors, by which investors do not view the precise types of the VCs' projects and learn the outcomes only with delay; and (iii) the limited liability of the VCs, which puts a wedge between the incentives of VCs and investors. Elements (ii) and (iii) are new contributions to the literature on belief cascades.

As each VC observes its fellow VCs' investment decisions, it infers that those decisions are based upon its peers' private signals. If a pattern emerges in its peers' investment decisions, each individual VC becomes more likely to discount its own private signal if it conflicts with the pattern. If this pattern is consistent enough, which occurs after a series of consecutive investments in the same size project, then this peer-derived information drowns out the information contained in the private signals completely. This is how a belief cascade forms. Consistent with the literature's definition of a belief cascade, at this point the VCs' decisions no longer depend on their private signals. The insights behind this reasoning were originally developed by Bikhchandani, Hirshleifer, and Welch (1992) and Banerjee (1992). See also Bikhchandani, Hirshleifer, and Welch (1998) for an overview of the literature on belief cascades, and Devenow and Welch (1996) or Hirshleifer and Teoh (2003) for a review of the literature on belief cascades in capital markets.

Of course, outcome information trumps inferences based upon investment decisions, so a cascade of this sort (a "primary" cascade) can occur only as long as VCs do not observe the outcomes of each others' investments. Proposition 1, in the Appendix, states that a primary cascade can occur if the lag with which VCs observe investment outcomes (T_1) is sufficiently large. Figure 1 depicts the evolution of VCs' beliefs on the simplex of probability distributions over the different types of opportunities. Based on the example developed in the Appendix, the point μ_1 (specifically, $\mu_1(L) = \frac{1}{2}$ and $\mu_1(S) = \mu_1(B) = \frac{1}{4}$) represents the common prior belief shared by all VCs and investors. This prior belief is in the region labeled $\{L, S\}$, where each VCs assumes that its opportunity is large unless it observes an S signal, reflecting the historical pre-game coordination that we describe below.[5] The succeeding points through μ_6 are the realizations of VCs' beliefs, given that each VC in periods 1–5 invests in an L project upon observing either a B signal or an L signal. By period 6, these beliefs have entered the region labeled $\{L\}$, in the bottom right of the triangle, in which any VC will make an L "bet" regardless of its private signal. That is, this region represents an L cascade. In this region, a VC is likely to make two types of errors. First, it will infer that an S opportunity is an L opportunity. Second, it will infer that an opportunity not worthy of investment is actually worthwhile. Hence, the model predicts that with such a cascade comes an increase in VC outlays.

We note that although in this example S projects and L projects are by construction equally profitable, we may reasonably assume that successfully implemented L projects would actually have higher returns than successfully implemented S projects, as GBF strategies are appropriate for winner-take-all markets. In Figure 3 we explore the effect of increasing the profitability of successful L projects. The figure shows that this change increases incentives for VCs—with their limited liability that protects them from the downside of failed investments—to make L bets relative to S bets, and thereby increase the size of the L cascade region at the bottom right of each figure. With this increase, fewer L signals are needed to initiate a primary L cascade.

Our theory describes conditions under which the probability of an L cascade increases when opportunities arrive randomly. In practice, we identify several historical forces that functioned a pre-game signals coordinating beliefs on a high probability that arriving opportunities will yield profits only as large projects, thereby increasing the likelihood of a series of initial large investments. First, however, it is helpful to articulate carefully the set of business decisions implied by the GBF strategy, which we model as large-scale entry.

2.2 Primary Cascade: History

In this sub-section, we provide evidence for Fact 1. The GBF strategy, in which firms tried to accumulate market share aggressively, was based on the presumption that there was a significant first mover advantage in internet markets. First movers, it was believed, would preempt later entrants, establish preferred strategic positions, and thereby secure supra-normal long-term returns. A necessary corollary of early entry was rapid expansion. Firms

[5] Without such pre-game coordination, starting from a uniform prior, a belief similar to μ_1 can be reached after several consecutive realizations of L investments. The computational burden of these additional periods on the simulation of investors' beliefs is heavy, and so we find it both convenient and historically relevant to choose a prior belief that already favors L projects.

following a GBF strategy tried to grow aggressively and make substantial investments to both acquire customers and preempt competition (Afuah and Tucci 2003; Eisenmann 2002; Reid 1997).

In theoretical terms, GBF was justified by anticipated scale economies and network effects that led to "first mover advantage" (FMA). The intellectual basis for FMA and the GBF strategy it supports has been developed within academic circles over many years. Tirole (1988; p. 315) summarizes the literature on preemption associated with the commitment value of sunk costs, and, of course, the Stackelberg game was introduced in 1932 (Heertje 1996). A goal of this literature has been to understand under what conditions a preemption strategy works, and so to better understand competitive behavior. Bridging between this theoretical literature and practical business application, Lieberman and Montgomery (1988, 1998) showed how these conditions might be interpreted in more realistic situations. However, the nuances of these debates did not carry over into the realm of business policy. In a study of the spread of the idea of FMA during the late 1990s, Bolton and Heath (2005) find, for instance, that FMA is interpreted much more positively in the business press than in the academic literature from which it emerged. For example, writing in the *Harvard Business Review* in 1990, Prahalad and Hamel emphasized advantages in being first to develop core competencies. While such claims did not go entirely unchallenged (cf. Tellis and Golder 1996), and some of these challenges were picked up by the business press (*The Economist*, 3/16/1996, "Why first may not last", p. 65), Bolton and Heath (2005) demonstrate that dissent was rarely publicized. [6] Moreover, their survey research among a sample of business decision makers found a positive correlation between media exposure and the belief in a strategic advantage of being a first mover, reinforcing the hypothesis that uncritical media coverage of FMA influenced managerial intent. Managerial belief in FMA is epitomized by Toby Lenk, CEO of the now defunct e-commerce startup eToys.com, quoted in the November 1, 1999 issue of *Newsweek* as saying "There is all this talk about [competitors] Toys 'R' Us and Wal-Mart, blah blah blah. We have first mover advantage, we have defined a new area on the Web for children. We are creating a new way of doing things. I am the grizzled veteran at this thing."

In practice, sufficiently strong network effects should reward FMA and make GBF a wise strategy (Arthur 1989; David 1985; Farrell and Saloner 1985; Katz and Shapiro 1985, 1986, 1994). Despite a lively debate in the academic literature (see, for example, Liebowitz and Margolis 1990), these ideas began to gain traction in the 1990s. At this point, some academic authors popularized these theories for the business community (Arthur 1996; Shapiro and Varian 1999).[7] The detailed mechanisms underlying the emergence of these ideas are less

[6] References to popular press sources appear in the text; references to academic sources appear in the bibliography in the standard format.

[7] See Filson (2004) for a similar but more limited analysis that components of a GBF strategy were

important for our purposes than the mere fact of their existence. In our model, these events would have coordinated beliefs on a higher probability of L opportunities. In Figure 1, this implies that initial beliefs would have been located closer to the L cascade region in the bottom right.

Proposition 1 is conditioned on a large T_1, i.e., that there not be feedback as to the wisdom of decisions for a sufficiently long period of time to allow a belief cascade to propagate. A widespread belief in FMA contributes to this delay, since if potential later entrants believe in FMA then they will hesitate to enter, making GBF self-reinforcing in the short run. Once GBF is debunked, however, entry into occupied markets can adjust to the realities of efficient scale. In the case of the Internet, the viability of the GBF strategy was unknown until firms failed to meet profitability expectations during the 1999 Christmas season. For example, there is ample evidence that GBF criteria such as web traffic measures predicted stock market valuation of internet firms over and above traditional evaluation criteria during the period (Hand 2001; Rajgopal, Venkatachalam, and Kotha 2003; Trueman, Wong, and Zhang 2000). The release of information about their operating results in early 2000 contributed to the stock market decline.[8]

The irony of GBF is that it took time to grow quickly. During the Christmas season of 1998 e-commerce firms met or exceeded expectations. Based on a review of major news outlets, public expectations regarding e-commerce for the Christmas season of 1998 concerned top-line revenue growth and the ability of firms to attract customers to the online marketplace. Profitability was not expected as the viability of emerging e-commerce fulfillment systems was still being explored. In a *Newsweek* cover story entitled "Xmas.com" (12/7/98), Jeff Bezos, founder and CEO of Amazon.com, declared "it's going to be a web Christmas." Online sales for 1998 were initially predicted to be $2.3 billion by Jupiter Research, a number that was widely cited, and reports of actual sales exceeded these expectations (*St. Louis Post-Dispatch* 12/19/1999, "For Online Stores, It's all over but the Shipping and Counting"). Importantly, profits were *not* used as a metric for success following the Christmas season of 1998. Rather, evaluations were based upon numbers of customers and gross revenue, criteria which established whether there was demand for on-line purchasing services, not whether it was profitable to pursue them (cf. *Newsweek* 11/1/2000 or *Venture Capital Journal* 6/2000, p. 44). Rarely did articles in *Newsweek*, *U.S. News and World Report*, *Business Week* and similar magazines mention the costs of sales, profit margins, or any data related to the

commonly pursued.

[8]Ofek and Richardson (2003) provide evidence that the decline was due to inefficiencies in the stock markets. In particular, they attribute the rise in the stock market to institutional barriers, to shorting of stocks, in particular, to restrictions on insider stock sales due to lock-up provisions. Their analysis identifies a mechanism limiting the ability of investors to act upon knowledge about the true state of the e-commerce marketplace. As it happened, lock-up restrictions lapsed together with the arrival of information concerning the viability of e-commerce enterprises.

prospective profitability of internet businesses. Moreover, there is confusion about revenue and "making money" in statements such as "The $2.3 [billion] figure sent a message: Companies are making money out there in cyberspace…" (*Fortune*, 3/15/1999, pp. 114–115), when, of course, the companies were generating revenue but losing money.

The press reported that the takeaway lessons from 1998 were about preparedness, fulfillment, and meeting consumer expectations. Thus in the run up to Christmas 1999 the public discussion focused on the different components of implementing a GBF strategy. This discussion included such issues as the "necessity" of doubling and trebling server capacity to accommodate expected increases in web traffic, massive investments in advertising money to establish market presence and increasing investment in customer service capabilities to, for instance, enable realtime online support, shorten average email response time, and ensure timely fulfillment (cf. *Business Week* 11/1/1999, *Brandweek* 12/6/1999 p. 64, *Internet Week* 8/16/1999, p. 1, *Inter@ctive Week*, 12/13/1999, 6(51) p. 72): "Retailers were caught off-guard by last year's online Christmas crush. Many experienced site outages and product shortages, while others failed to recognize the potential of e-commerce and didn't establish an online presence in time or at all. This year, however, 'They've had due warning. They have no excuses,' [Jupiter Research analyst Ken] Cassar says." (James, Dana, "Merr-E Christmas!" *Marketing News*; 11/8/1999, 33(23), pp. 1–16)

There was a general anticipation of the coming shakeout in e-commerce well in advance of the Christmas 1999 results. For example, Timothy M. Halley, a venture capitalist with Institutional Venture Partners, was quoted in the November 1, 1999 issue of *Business Week* as saying "We're interested in industry leading dominant plays. Number one is great, number two is pretty good, and number three is why bother[.]" In the same article, the CEO of upstart Pets.com, Julie Wainwright, predicted that "consumers are going to vote and leave a lot of businesses behind during the holidays. It's going to be a make-it-or-break-it Christmas." On December 28th, 1999, Forrester Research Analyst Lisa Allen was quoted in the San Francisco Chronicle as saying "E-commerce is past the experimental stage, but it's not completely shaken out yet." It was becoming clear that it would soon no longer be possible to attribute lack of profits to difficulties in implementing a GBF strategy. These quotes appear representative of sentiments communicated widely in the popular and industry press (see also Stephen Lacy, 2000, "E-Tailers Initial Public Offering Plans Hinge on 1999 Christmas Sales" *Venture Capital Journal*, January 40(1) pp. 5–6).

E-commerce revenues during the 1999 Christmas season doubled or trebled their 1998 levels (*Electronic Advertising & Marketplace Report*, 1/11/2000). However, consistent with the tenor of the press in late 1999, substantial questions were raised about profitability (*Electronic Advertising & Marketplace Report*, 1/11/2000). We conclude from this short historical discussion that there was a widespread suspension of traditional evaluation criteria of internet firms during the late 1990s. We conclude that one primary condition identified by the model, that there not be information regarding the viability of investments, was fulfilled through early 2000.

Of interest we note that the analysis suggests that economic theory, in this case the popularity of theories of path dependency and increasing returns to scale led to a massive misallocation of funds during the period. In this sense, theory had a negative implication for practice.

2.3 Secondary Cascade and Investor Withdrawal: Theory

If $T_1 < T_2$, then there will be a period during which projects' realizations are known to VCs, but are yet unknown to investors. In our example, an L cascade occurs before the VCs have a chance to observe the outcomes of the early L projects. However, once they start to observe that these early L projects have failed, they become less likely to infer that newly arriving opportunities are L opportunities. During the L cascade, the VCs cease updating their beliefs because the mimetic actions they observe each other taking are uninformative. So during the cascade, their beliefs remain only marginally inside the L cascade region. Hence it takes just one L project failure to break the cascade. If the next signals following these failures are S signals, then the likelihood of a "secondary" S cascade increases.[9] The fragility of cascade beliefs to the arrival of new public information is a robust result in the literature on belief cascades, and indicates that the VCs' group behavior is liable to shift dramatically and unpredictably.

Once a primary L cascade is broken by the failures of early L projects, a secondary cascade forms after the next several VCs invest in a series of S projects. We show this formally in Proposition 2, in the Appendix. The movement of beliefs from the L cascade region, $\{L\}$, to the S cascade region, $\{S\}$, is depicted in Figure 2. Based on the example developed in the Appendix, the figure shows that a series of four failures of L projects combined with three consecutive S signals is sufficient for beliefs to reach the S cascade region, where any VC will make an S bet regardless of the nature of its own private signal.[10]

While the S cascade is forming among the VCs, the investors are also beginning to learn about the failures of early projects. We model the information asymmetry between VCs and investors in two ways: investors do not learn about the success or failure of the period t project until period $t + T_2$, and investors cannot tell the difference between S projects and

[9] Alternatively, if the next signals following the failure of an L project are L signals, then L bets would continue and beliefs could eventually push back into the L cascade region. That is, the breaking of a primary L cascade might not be observable even to a historian (much less to the investors in the model), since the breaking of an L cascade does not imply that L bets cease.

[10] Again, in this example S and L projects are symmetric in their profitability. In Figure 3, we show how increasing the profitability of L projects affects the evolution of beliefs between a primary L cascade and a secondary S cascade. The effects are subtle and don't yield any obvious regularities.

L projects. That is, they can observe whether or not VCs invest in startup firms, but they do not observe the differences among the strategies of different startups. Hence when investors observe the failure of the early L projects, they know only that those projects were not B projects. Still, the investors fully understand the information structure faced by the VCs, so they understand that the VCs will have already adjusted their investment strategies to account for the early failures. In the example, even after several project failures the investors still prefer to invest their funds with VCs rather than invest in bonds directly.

However, investors also understand the structure of VCs' incentives. In our model, VCs earn a percentage of the returns they generate, but do not lose any of their own capital if the project fails. That is, they face no downside risk, making them effectively risk-loving with respect to project outcomes, whereas investors are risk neutral. So investors may be worried that VCs are taking on too much risk by investing in S or L projects under conditions in which investors—if there were no informational asymmetry—would choose bonds. The implication of the informational asymmetry combined with the misalignment of investor and VC incentives is that after investors observe enough project failures, they infer that it is no longer worthwhile to invest in venture capital. In our example this occurs in period 11, after investors have observed four project failures. Result 3, in the Appendix, explains why we consider this a general phenomenon under appropriate conditions.

Figure 4 displays the timeline of events in the example—the signals and actions of the VCs and the observation of outcomes by VCs and investors—together with the investors' expected profit from providing their funds to VCs rather than investing directly in bonds. During the primary L cascade, investors' expected profits rise gradually as they observe VCs investing in startups each period. Investors' expected profits jump up in period 7, when they know that VCs are learning new information from the outcome of the period 1 project. Starting in period 8, and continuing through the secondary S cascade, investors' expected profits fall as they observe the failures of the early projects. The expected profits fall below zero in period 11, when investors first withhold their funds from venture capital.

Perhaps ironically, the investors start to withhold their funds even as the VCs are adjusting their strategies to take the early failures into account. During the time leading up to the secondary S cascade, the VCs have learned more about the state of the world and are more likely to be making good investments. At the time investors pull their funds out of venture capital, these projects have not yet reached maturity. In our example, all the projects leading up to the secondary S cascade succeed, and once their success becomes public the investors return their funds to venture capital. This is shown in Figure 4, where the investors' expected profits from investing in venture capital become positive again in period 14, when they observe the success of the first project started after the primary L cascade was broken. As they observe further successes, their expected profits continue to increase.

Result 4, in the Appendix, explains why we think this should be a general phenomenon.

To generate the secondary S cascade we rely on the assumption that VCs observe project outcomes before investors, and that the projects started after the breaking of the primary L-cascade were all S projects that were well-matched to their opportunities. In the next section we review evidence that suggests that VCs and other insiders realized that GBF was inappropriate before other investors. However—stepping back from the model—there are two other ways that VCs' beliefs can shift to favor smaller projects without relying on a string of successful small projects. First, if we were to relax the assumption that opportunities are drawn from three states and instead think of each opportunity (and its related signal) as being drawn from a larger space, then even as an L cascade is occurring, there can be some small investments made in response to opportunities that get very strong S signals. This then would yield a small population of early S projects, which would be disproportionately successful because they operated under almost-certainly-optimal strategies. Second, and more importantly, ventures started under L strategies might have been able to switch to S strategies, at some cost, after the decline. If these ventures were able to succeed after switching strategies, then VC beliefs would be influenced in the same way as if these ventures had been started during a secondary S cascade.

One important restriction of our model is that investors' investment decisions are made simultaneously with the VCs'. If one were to think of the investors in the model as limited partners (LPs), then this would be an accurate depiction of the venture capital market. However, LPs are generally sophisticated institutional investors (Gompers and Lerner 2000), so we believe that the information asymmetry we hypothesize, in which LPs do not fully observe VCs' investment strategies, is unlikely to be an accurate characterization of the LPs' true information sets. In contrast, asymmetry between the VCs and the retail stock market to which they sell their offerings upon IPO is likely to be significant. As we describe in the Appendix, a model in which VCs take into account future retail market beliefs when making their investments would not be tractable because it would need to take into account the arrival of additional information about alternative projects between initial investment and IPO. Alternatively, in the current model interpreting the investors as IPO market buyers requires particularly heroic assumptions. However, we conjecture that qualitatively the beliefs of investors at time t in the model can be interpreted as the VC's reduced form estimates of retail investors' beliefs at time of IPO. Under this interpretation we are estimating IPO investors' beliefs based on less information than they actually have. Whereas IPO investors would observe the success or failure of projects that are currently underway, investors in our model do not. Unfortunately, this introduces some bias, since the information we are taking away is correlated with the current VCs' beliefs about the underlying state of the world. In general, what the additional information would likely do is bring investors' beliefs closer into line with VCs' beliefs, which could reduce their incentive to withhold funds, but would not affect the formation of cascades.

This richness of the model enables us to interpret events in the IPO and VC markets after early 2000 through the lens of our example. First, if VCs are able to observe the failure of the GBF strategy earlier than IPO investors, then VCs can start adjusting their investment strategies before the market reacts. Thus Proposition 2 suggests that there should be a decrease in deal size prior to the collapse of the securities prices. Second, due to the conflict of interest between VCs and investors, investors will withhold funds from venture capital once the failures of large numbers of GBF-era deals become public—even though the venture capitalists would rather continue investing. Thus Result 3 predicts a decline in the IPO market for internet related stocks, a decline in VC commitments, and a decline in total VC outlays. Third, if the projects that VCs initiated after adjusting their strategies but before investors withdrew their funds are successful, investors can observe these successes and reappraise the profitability of investing in venture capital. Thus Result 4 predicts that venture capital activity in the relevant sectors can rebound from the collapse of prices in the public markets.

2.4 Secondary Cascade and Investor Beliefs: Evidence

The historical record provides evidence of a secondary cascade in VC investment patterns, a reduction of investor support, and, more recently, the seeds of a revival. In this subsection, we present evidence in support of Fact 2.

Evidence that VCs soured on the GBF strategy prior to the market would support the hypothesis that T_2 was greater than T_1, and that a secondary S cascade may have occurred. Aggressive positions of insiders before March 2000 lead Schultz and Zaman (2001) to infer that insider and market beliefs did not diverge at that time. Based on a systematic examination of the subsequent expiration of lock-up agreements and contemporaneous stock market movements, Ofek and Richardson (2003) conclude that the stock market decline was precipitated when insiders became more likely than stock market investors to believe that valuations were overly optimistic. Together, these findings suggest that there was a divergence in investor and VC beliefs by March 2000, after it became clear that few internet firms profited from the 1999 Christmas season. Proposition 2 relies on such a condition to generate an S cascade.

General trends in the venture capital market are consistent with these predictions. Consistent with the occurrence of primary and secondary cascades, we see a rise and fall in average investment size in IT and internet sectors but not in others. In Figure 5, deal sizes are indexed to one in the first quarter of 1996, all amounts are adjusted for inflation. We report the deal sizes by industrial category of the target firms as classified by Venture Economics and compare investments in internet and other IT firms to those in biotechnology and non high-technology firms. Investment sizes rose sharply from the first quarter of 1996, almost quadrupling in both internet- and IT-related deals by the summer of 2000. In both these sectors, by the middle of 2002 investment sizes had dropped to pre-boom levels. While a similar rise and fall can be seen in non-high technology sectors, the effect is not nearly as pronounced. Since Figure 5 reports a mix of all rounds, one might be concerned that this increase is driven by sizable later-round investments in early, successful internet firms. To establish the pervasive nature of the phenomenon, Figure 6 reports the three-quarter moving averages for first round deal sizes.[11] The data exhibit a similar pattern to those reported in Figure 5.

Consistent with Result 3, while venture-backed IT-related investment did not dry up entirely after the March 2000 decline in stock prices, fund commitments and the IPO market underwent dramatic changes. Internet-related VC fund commitments dropped by a factor of 53, from $15.1 billion in the fourth quarter of 1999 to $283 million in the third quarter in 2001 (Figure 8). Internet-related IPOs peaked at 44 in the third quarter of 1999 and dropped to zero in the fourth quarter of 2000 (Figure 7).

It is still too soon to tell if there is a broad revival in internet-related investment as Result 4 predicts. Ten VC-backed internet firms had successful IPOs in the fourth quarter of 2004, representing the highest level since the third quarter of 2000. Data on venture commitments are available only through 2003, and no upward trend is apparent.

These figures also show that the closing of the IPO window and the suspension of limited partner commitments was not immediate. In the second and third quarters of 2000, 27 VC-backed internet firms had IPOs, and VCs raised $16.5 billion for new investments. It took time for the signals of failure to counteract the legacy of the belief cascade. In terms of the model, this can be interpreted as the string of three periods in which VC beliefs migrate through the $\{L, S, B\}$ region, as depicted in Figure 2.

2.5 Too Little Entry

Stepping outside the formal model, we note that it would be surprising if venture and investor beliefs associated with the GBF cascade did not also influence entrepreneurial decision-making. Market entry is one of the most fundamental decisions facing a potential entrepreneur. A belief in GBF coupled with the existence of an early market entrant would likely serve as an ex-post, imagined barrier to entry for any would-be entrepreneur.[12]

[11] Moving averages are presented due to much higher volatility in first round funding amounts than all round funding amounts.

[12] A robust result in industrial organization economics is an inverse relationship between minimum efficient scale and the number of firms entering a market. See, e.g., Caves, Khalilzadeh-Shirazi, and Porter (1975), Audretsch and Mahmood (1994), Geroski (1995), and Mata and Portugal (2002).

An additional source of scarcity is needed to produce this result in a formal setting. In the presence of such a constraint, too little entry is a direct consequence of a cascade on GBF.

This result is commonly generated by assuming fixed demand, but in fact, supply side constraints are also potential limiting factors. For instance, on the demand side, if the number of markets that could be entered were limited, then either a small number of large entrants or a large number of small entrants would result. If small were optimal but large were chosen, there would be too little entry as VCs invested in large projects to the exclusion of more numerous smaller projects. On the supply side, the large investments associated with GBF would have driven up prices in relatively inelastic factor markets, rendering otherwise profitable opportunities unprofitable. For example, there were substantial increases in IT-related employment growth rates and personal income per capita as the public markets appreciated, and substantial decreases after they declined (Daly and Valletta 2004).

This logic supports a counter-intuitive twist on the influence of a GBF belief cascade on entrepreneurial activity. If GBF belief proved ex-post incorrect, then this imagined barrier to entry may have *decreased* the number of firms entering during the Dot Com era.

Our model also shows how too little entry can be perpetuated beyond the end of the Dot Com era. Even after VCs and entrepreneurs adjust their entry strategies upon learning that GBF was ill-advised, investors cease funding VC investments, and entry dries up due to a lack of capital. This, too, is a supply-side explanation, but one driven by a shortage of investor optimism.

Empirically, if the too-little-entry hypothesis is correct, controlling for the incorrect pursuit of GBF, we should see high survival rates for those firms that did enter. It is important to note here that "failure" of a firm in the eyes of investors does not necessarily correspond with exit of the firm from the market. Failure from the perspective of investors means that their equity stakes in VC-backed projects did not provide the rate of return that they expected when making their initial investments. Such failure is compatible with survival, and even profitability. The key element of failure is that it reduces investors' beliefs about the returns to similar investments in the future. In the model, early L projects must fail in order to break the L cascade, but the firms that arise from these projects may exhibit enhanced survival rates ex post due to a less-than-optimal number of competing firms. (In this paper, "failure" refers to failure from the perspective of investors while "exit" refers to exit from the market.) In spite of the prevalence of venture capital and other private equity, the majority of firms did not pursue GBF, whether by choice or by necessity. Hence we should see that survival is either negatively related or unrelated to the receipt of VC support and the implementation of GBF. However, it is reasonable to expect this effect to be confounded by the presumption that VCs match with higher quality entrepreneurs than other financiers. Therefore, inappropriate pursuit of GBF might be counteracted to some extent by otherwise good decision making.

Finally, if investors eventually return their funds to venture capital, as predicted by the model, then there may be a resurgence of VC-backed entry into these markets, but at a more appropriate scale. This added competition should be expected to put a damper on the future survival rates of the Dot Com-era firms.

The too-little-entry hypothesis contrasts with a "cascade-driven over-entry" hypothesis, where a GBF cascade might, on the margin, lure entrepreneurs from wage employment.[13] The data may help us distinguish between these two competing hypotheses. If these marginal entrepreneurs were pursuing evanescent opportunities, then exit rates of Dot Com startups will be high. In contrast, the too-little-entry hypothesis predicts low exit rates in the presence of low post-entry competition.

Another contrasting hypothesis is that GBF was indeed the correct strategy for most Dot Com markets, perhaps due to large fixed costs necessary for survival, but the operating profits gained from GBF were not sufficient to justify the initial investments. This hypothesis would suggest that the surviving firms should be large but not very profitable, and should face little threat of entry, implying that survival of firms should be highly positively correlated with the sizes of their initial investments. In contrast, the too-little-entry hypothesis implies a negative correlation (subject to the counteracting forces discussed above). A second contrast is that the too-little-entry hypothesis raises the possibility of a resurgence of VC-backed entry into internet-related markets while the "large fixed costs but low profits" hypothesis implies that there should be no such resurgence.

3 Data and Analysis

We test these hypotheses exploiting a subset of the data first introduced by Goldfarb et al. (2005). These data are drawn from the Business Plan Archive (BPA) and are derived from 1,142 funding solicitations to a single venture capital fund.[14]

[13] In the language of our model, during an L cascade, we would also expect to see a greater number of projects financed for two reasons. From the model, deals that were once classified as B become L deals, so we should see more investments. Reinforcing this trend, if we were to consider a more general equilibrium framework, and if L deals have higher expected returns, we should see an increase in startups as nascent entrepreneurs start companies in preference to the pursuit of wage employment. Selecting on VC funding, we can find support for this prediction. The Venture Economics database reports that through the second quarter of 1998, about fifty internet firms were funded each quarter. This number increased to 490 in the first quarter of 2000. By the second quarter of 2002, the number of firms supported had dropped to 1998 levels. A similar pattern is seen in non-internet IT firms, although the trend is less pronounced. The number of venture-backed biotechnology and non-high technology firms remained steady or increased slightly during this period.

[14] http://www.businessplanarchive.org/. We are careful to use the language "solicitation" as opposed to "firm" or "entrant" as many of the groups that solicited funding never moved beyond the planning stage of their ventures nor engaged in commercial activity, and hence should not be considered entrants. This sample is a sub-sample of 2,679 private equity solicitations received by this single VC during the period 1999–2002.

A key prerequisite for using these data to test hypotheses about the general population of internet firms during the period is to establish the representativeness of this sample. Goldfarb et al. (2005) exploit the fact that about 10% of the firms in this sample and 21% of the firms in a companion sample were financed by other venture capital firms. They then compared the VC-backed companies in both samples to the general population of VC-backed companies along several observable dimensions such as the number of funding rounds and the total funding received. They find that (i) the BPA oversamples internet related firms and (ii) in most measurable ways the VC-backed BPA companies are not statistically different from the general population of VC-backed information technology companies founded after 1993. They conclude that there is some evidence that the BPA is oversampling lower quality internet startups. This potential bias implies lower survival rates and works against the too-little-entry hypotheses.

For the purpose of the analysis below, we narrow the sample further by employing two criteria. First, to evaluate the too-little-entry hypothesis, we compare survival rates across multiple emerging industries. Prior studies have employed substantial entry hurdles to generate survival statistics. For example, in their study of automobiles, Raff and Trajtenberg (1995) include only those firms that displayed automobiles in auto shows. This distinguished groups that never got past the planning stages from groups that actually produced a product that could be purchased. Similarly, in their study of survival of U.S. manufacturers, Dunne et al. (1988) include only plants that were built and functional. In our setting, we seek, therefore, to exclude ideas that never progressed beyond the business planning stage. Hence, we classify a firm as an entrant if and only if it built a website and a product or service was available for purchase. According to this criterion, 212 of the 1,142 firms never entered. Second, we categorized the businesses in our dataset according to the Afuah and Tucci (2003; chap. 6) classification of internet business models. An internet firm is defined as any firm with a revenue model that relied on the internet. In our sample, 1,003 of the 1,142 firms were internet firms by this criterion. Of these 1,003 internet firms 205 were also classified as never having entered. A further ten observations were lost due to incomplete data. The analysis below pertains to the remaining 788 firms.

3.1 Survival Rates

We now turn to an analysis of survival in which we present the evidence in support of Fact 3. We measure survival of firms in our sample through 2004. We use the survival criteria for

The venture capital fund was established in 1999 in the Northeast and managed $75 million. The fund was affiliated with a leading internet portal and saw itself as seeking business ideas that proposed to exploit the commercial potential of the internet.

internet firms developed by Goldfarb et al. (2005).[15] Our limited dependent variable *survival* takes the value 1 if the service described in the solicitation of the focal VC was still offered by the same or an acquiring legal entity in 2004. We find that 48% of the businesses originally described in the solicitations survived through 2004.[16]

Was the shakeout more severe in the internet industry than in other nascent industries? To answer this question, we compare the observed survival rates of internet technology ventures to the survival rates in four other emerging industries: automobiles, tires, televisions and penicillin (Simons 1995). We report the exit rates and Kaplan-Meier exit function estimates in Table 1.[17] The table pools entry cohorts and adjusts for left censoring. The first column reports the number of firms at risk for each age group while the second column reports the number of exited firms of that age. *Net lost* refers to the number of firms that

[15]Goldfarb et al. describe several challenges in determining exit. When no website was accessible, exit was suspected. This was confirmed and the precise time of exit was dated through the Internet Archive, which catalogues snapshots of websites since 1996. In some cases, a website was operational but was clearly not affiliated with the company represented in the planning documents. Generally, cross referencing the information in the Internet Archive with the information in the planning documents was sufficient to confirm this and date the exit of the original firm. A second problem was acquisitions. Acquired companies were classified as survivors, although great care was taken in verifying that the acquisition occurred prior to any bankruptcy. Such occurrences were identified by triangulating information from the Internet Archive, Google web searches and Lexis-Nexis searches. A more formidable problem is posed by "living dead" websites, which are cases in which a website is still operational but the company has clearly exited. For example, there are several instances of still-functioning websites that have not been changed since the 1990s. In these cases exit was dated to the last website change in the Internet Archive. We note that in our context this is a conservative coding decision, as Goldfarb et al. erred on the side of coding survivors as exits and moreover likely pre-dated exit. Both types of errors would lead to an overestimate of annual exit rates. Finally, website owners can block Internet Archive access to their website. In 63 cases, both the current website and the archived versions were blocked. Thus, while these firms were classified as exits, their exit could not be dated. In the analysis that follows, we randomly assign exit dates from 2000 through 2004 for these firms. This has an effect of smoothing the measured hazard rates. Omitting these firms from the sample does not (qualitatively) affect the hazard estimates below.

[16]A possible bias vis-a-vis other survival studies is our classification of merger as survival. First, in studies of exit rates of manufacturing plants, acquisitions are classified as exits (cf. Agarwal and Audretsch 2001; Dunne, Roberts, and Samuelson 1989), so by comparison we are biasing our analysis upwards. Second we note that an acquisition may not indicate that a firm would have been capable of surviving if the acquisition had not occurred, since distressed businesses might be purchased for discount prices. We do not believe this to be a significant source of bias, as only 57 firms classified as survivors in our sample were acquired. Attempts to review the historical record of these firms' transitions to evaluate the nature of the acquisitions were unsuccessful as *all* acquisitions were given positive spin.

[17]The Kaplan-Meier estimator is a non-parametric estimator of cumulative exit rates that takes into account right censoring (see Kiefer 1988 for an in-depth treatment). Absent right censoring, a reasonable survival rate estimator $\hat{S}_t$ equals the number of firms surviving more than t years divided by the sample size N. To take into account right censoring, we need to remove the right censored firms in the calculation of the annual survival rates. The Kaplan-Meier estimator does precisely this. Let d_t be the number of firms that exit at age t and m_t be the number of firms we do not observe beyond their tth year. Firms are at risk of failure if they have not failed or been censored. Define r_t to equal the number of firms at risk at age $t-1$: $r_t = \sum_{\ell \geq t}(d_\ell + m_\ell)$. Let T_j be the exit date of firm j; then the hazard $\lambda_t = \Pr[T_j = t | T \geq t]$ is the probability that a sample firm will exit at age t conditional on surviving to age t. An estimator of the hazard is $\hat{\lambda}_t = \frac{d_t}{r_t}$. The Kaplan-Meier estimator of the survivor function is the sample analogue: $\hat{S}_t = \Pi_{\ell \geq t}(1 - \hat{\lambda}_\ell) = \Pi_{\ell \geq t}\frac{r_\ell - d_\ell}{r_\ell}$. The Kaplan-Meier exit function is $1 - \hat{S}_t$.

enter the observation window net of firms that exited. For example, the −52 in row 1 refers to the 72 firms that we observe only from their second year of operation net the 20 that exited in their first year. After five years, 47% of firms have exited. Hazard rates of firms of age eight and above are suspect due to severe right censoring. In fact, these firms, were founded before the Dot Com phenomenon began. In Table 2 we report cumulative exit rates by exit year for entry-year cohorts. We also report the cumulative exit rate in our sample, the number of firms that operated at any time during a given year, the number of exits and the exit rate. We pool all 54 pre-1997 entrants. We find an (unweighted) average exit rate of 14% conditional on surviving through 1999. The exit rates by year are between 6% and 15% from 2000 through 2003 and 19% in 2004. There is a jump in exit rates for all cohorts in 2000, reflecting the reimposition of traditional evaluation criteria. This fact is consistent with a key condition identified by our theoretical model: the absence of a profit-based performance feedback mechanism in the early years of the industry.

We now compare this exit rate to exit rates in other emerging industries.[18] Annual exit rates for autos during 1900–1909 averaged 15%, 21% during the 1910–1911 shakeout and 18% during the period from 1910–1919. The annual exit rate from the tire industry during 1905–1920 averaged 10%; it was 30% during the shakeout in 1921 and 19% during the period from 1922–1931. The exit rate from the television (production) industry was 15% during the period 1950–1952. Finally, the exit rate from the penicillin industry was 5.6% during the period 1943–1954 and 6.1% during the period 1955–1978. These numbers suggest that the exit rate for Dot Com firms is in line with other emerging industries, or perhaps lower. Moreover, this comparison is biased against our hypothesis due to the fact that we do not observe entry after 2001. Previous studies on industry evolution demonstrates that entry continues during and after shakeout periods. Indeed we observe that entry occurs throughout 2000 and 2001. Our inability to see entry after 2002 implies that we overestimate exit rates in the general population. For example, in the case of television manufacturers, ignoring entry after the shakeout in 1952 systematically biases the hazard rate upwards by a factor of at least two, and, as expected this number increases as the time window widens.[19] From this comparison we draw two conclusions. First, the initial shakeout for Dot Com firms occurred earlier than in other emerging industries. Second, with the exception of the penicillin industry, the average exit rate among internet entrants appears comparable to or lower than other emerging industries. This evidence supports the model's prediction that survival rates should be high among Dot Com-era firms.[20]

[18] The data from other industries do not suffer from censoring problems. Hence those exit rates are the Kaplan-Meier estimates.

[19] Authors' calculations. We thank Kenneth Simons for making the television industry data publicly available.

[20] Although this number is approximately 50% higher than the exit rate of manufacturing plants, we do not believe that is a meaningful comparison as manufacturing plants are likely to require significantly more

3.1.1 Private Equity, Entry Size, and Survival

We now turn our attention to the question of whether the receipt of private equity funding increased survival rates (Fact 4). The model suggests that receipt of venture capital funding during this period was intended to support the implementation of an (incorrect) GBF strategy. Therefore, we should expect to observe high failure rates for those firms that pursued this strategy. Our data include many firms that pursued a GBF strategy, as evidenced by their funding levels. However, the strength of our contribution hinges on the fact that we also observe a great number of firms that did not pursue a GBF strategy, either through choice or through an inability to secure VC financing. Such firms that did not follow the GBF strategy, conditioned on quality and ex-post inviability of GBF, would be expected to succeed at higher rates. Since failure of GBF implementation is associated with (but does not imply) exit, survival rates should be either negatively related or unrelated to entry size. This implication sits in contrast to predictions of other theories and evidence regarding entry size and private equity financing.

We first report the survival rates of sample firms conditioned on private equity financing in Table 4. We separate the firms into categories according to funding levels. We find that there is little difference in survival rates across funding categories, with the possible exception of firms in the top 5th percentile of funding. We will see, however, that this is not robust in the multi-variate analysis after controlling for entry cohort. Very few that entered after 2000 received high levels of funding. That is, these high survival rates could be attributed to the higher survival rates of early entrants, not to scale of entry.

We relate the exit hazard to the receipt and amount of private equity using a piecewise-constant proportional hazard model that assumes an exponential parametric survival distribution with a semi-parametric piecewise baseline hazard. See Kiefer (1988) for a primer on the analysis of duration data. We follow Wooldridge (2002, p. 709) closely in our exposition of the empirical model. The exit hazard, defined as the probability that a firm will exit in a given year conditional on surviving to that year for an individual firm-year observation is

$$\alpha_t(x_j, \beta) \equiv \exp[-\exp(\beta' x_{jt})\lambda_t]. \tag{1}$$

where λ_t is the baseline hazard for period t, and, for each of j firms, x is a vector of possibly time-varying explanatory variables. In our case, the important time-specific variation is the arrival of private equity funding. We estimate a separate and constant baseline hazard for

investment and these investments likely occur later in firm—as opposed to plant— life (Dunne et al. 1988). We further note that our finding is subject to the following caveats. On one hand, we necessarily observe survival only through 2004. A wave of exits since this time would decrease our survival estimates. On the other hand, we do not observe entry after 2002. If we were to observe such new entrants we would measure higher survival rates.

each age, measured in years, that a company is at risk of failure. This allows flexibility in the shape of the baseline hazard:[21] If for observation j uncensored exit occurs in year T_j, the likelihood function can then be written

$$\left[\prod_{t=1}^{T_j-1} \alpha_t(x_j, \beta)\right] [1 - \alpha_{T_j}(x_j, \beta)] \tag{2}$$

The first term is the unconditional probability that firm j will survive through period $T_j - 1$ while the second term is the probability of failure at time T_j. If the firm survived beyond our temporal window, the likelihood function consists of only the first term and $T_j - 1$ is be replaced by T_j which represents the age of the firm at the end of that year.

If d_{tj} takes the value 1 when the duration t for observation j is uncensored, the log likelihood for observation j can be written as

$$\sum_{t=1}^{T_j-1} \log[\alpha_t(x_j, \beta)] + d_{tj} \log[1 - \alpha_{T_j}(x_j, \beta)] \tag{3}$$

The log likelihood for the entire sample is attained by summing Eq. 3 over all observations.

An important advantage of our data is that we observe not only VC funding, but also other private equity funding as well, including angel and insider financing. In our analysis we seek to distinguish between VC and other private equity investment, as these types of financing may be associated with systematic differences across firms.[22]

We report summary statistics in Table 3. As independent variables we provide several measures of private equity funding. The dummy variable *Private equity* flags firms that received any private equity funding. In the sample, 41% of the firms received private equity. The dummy variable *Venture financing* flags firms that received VC financing any time through 2004, as reported by the Venture Economics database. In the sample, 14% of the firms received VC financing. For firms that were financed, we do not observe VC financing amounts for 11 firms and and do not observe angel or insider amounts for an additional 13 firms. Conditional on observing the amount of financing, the average total financing was \$4.1 million. Goldfarb et al. (2005) find that non-VC financing rounds are almost exclusively first round financings, that non-VC financing rounds are smaller than first round VC financings, and also that firms that received VC financing tended to receive more financing dollars than non-VC supported firms. Similarly, in our sample, conditional on receiving VC financing the average financing amount is \$23.5 million (113 firms, s.d. \$33.5 million) while conditional on receiving non-VC financing, the mean financing amount is \$2.8 million

[21] The basic results are robust to other specifications.

[22] See Goldfarb et al. (2005) for a broader discussion of these differences and their importance in this sample.

(224 firms, s.d. \$4.8 million). Thus the distribution is highly skewed. The 75th percentile of all funding is \$1.2 million, the 90th percentile is \$9.4 million, the 95th percentile is \$25 million, and the 99th percentile is \$69 million.

There is evidence that different cohorts will have different survival hazards in emerging industries (cf. Klepper 2004). We include a set of dummy variables for year of founding to control for cohort effects. We identified the first cohort as firms founded before or during 1996, the second cohort as firms founded between 1997 and 1999, and the final cohort as firms founded (roughly) after the stock market decline, i.e., during or after 2000.[23]

Finally, as additional controls we include information on the revenue models that the firms proposed in their business planning documents. Following Afuah and Tucci (2003), we classify firms into seven broad categories of revenue models: advertising, subscription, markup (i.e., internet retailing), production, referral, fee for service, and commission. We provide brief explanations and examples of firms in our sample for each of these revenue models in Table 5. The mean number of revenue sources per firm is two, although there are some that described up to six. The most common revenue model listed was fee for service (62%), followed by advertising (36%), production (26%), subscription (25%), commission (23%), markup (18%), and, finally, referrals (13%). We note that there was little knowledge as to which revenue model was appropriate in the new internet space.

We report the results of a series of models following Eq. 1 in which we measure exit hazards for the 788 internet firms in our sample in Table 6. Hazard ratios are reported. Significance at the 1%, 5%, and 10% levels is noted by symbols **, *, and +, respectively. Firms are left censored from the later of 1997 or their founding date, and right censored after 2004. Thus, we estimate eight baseline hazards (λ_t in Equation 1). For controls we include revenue model dummies, a count of the number of revenue models, two cohort variable controls and a dummy variable that turns on after 1999. In Model a, we include *Ln private equity funding*, which is the natural log of the total amount (measured in thousands of dollars) of private equity funding the firm received through that year.[24] There are many firms that received no funding. As opposed to adding an arbitrary value to these zeros before taking the natural log, we set the log of zero values to zero, and then include an additional dummy variable that takes the value of 1 for these observations (*Dummy: zero private equity*). The regression reports the main result of this subsection: there is no measurable relationship between private equity funding and survival. In particular, the measured hazard ratio for *Ln private equity* is 0.979, and the robust z-statistic of this estimate is 0.56.

It is possible that we fail to observe an effect of financing because we are mixing venture

[23] Imperfect dating of exit precludes more precise cohort identification to account for the fact that the stock market decline began in March of 2000 and continued for several months.

[24] We take the logarithm due to the skewed distribution of financing received. The results are qualitatively similar without taking the logarithm.

funding and other private equity funding (presumably angel or insider financing). While little is known about angel financing in general (Goldfarb et al. 2005), we do suspect that on average it is a less sophisticated source of capital than VC financing. In Model b, we introduce a dummy variable, *Venture financing*, that flags firms that received VC financing on or before the tth year since their founding. Although the sign of this estimate suggests that VC-backed firms are less likely to exit (hazard ratio 0.77), the coefficient is not statistically distinguishable from zero (z-stat. 1.21). To further investigate whether the marginal influence of an additional dollar of VC funding on survival is different than the marginal influence of an additional dollar of non-VC funding, we include a separate term for VC financing with a corresponding zero value dummy in Model c (*Ln venture capital* and *Zero venture capital*, respectively). Although the hazard ratio on the main term is less than one, suggesting that VC money is associated with lower exit hazards, neither estimate is statistically distinguishable from zero. In Model d we investigate the robustness of the result of Model b to the removal of controls, and find that they have no influence. In Model e we replace the logarithmic function with a 5-part step function of the amount of financing received. We include mutually exclusive dummies for firms that received some funding but were below the 75th percentile in total funding, firms that were in the 75th to 89th percentile, firms that were in the 90th to 94th percentile, and firms that were at or above the 95th percentile of funding. The omitted variable represents firms that received no funding. None of these dummies is significant, nor are they jointly significant ($\hat{\chi}^2(4) = 4.61$).[25] As in other models, we also include a VC financing dummy variable and find it to be insignificant. Finally, in Model f we test whether there is any relationship in the data between survival and receipt of private equity or venture funding, regardless of the amount. Controlling for VC financing, we find that receipt of private equity funding *increases* the exit hazard by 22%. This is significant only at the 10% level.[26]

[25] In case the signal is extant, but simply very weak, we do note that the pattern is not monotonic. Firms that received no funds were more likely to survive than firms that received small amounts, but firms that received large amounts of VC funding were most likely to survive.

[26] In Model f, the private equity dummy flags the firms that are in the 59th to 100th percentiles in private equity financing. We might expect the GBF strategy to be more appropriate in some types of businesses than others. For instance, Owan and Nickerson (2004) find that under some conditions there are first mover advantages in business-to-business (B2B) exchange formation. To explore this possibility, in unreported regressions we exploit the business model information reported in Table 5 and interact the observed funding amounts with the revenue model dummies. Consistent with Dunne et al. (1989), we find weak evidence that high amounts of funding increased survival rates when the firms were engaged in production (i.e., manufacturing). Funding had no effect in other areas. Moreover, after allowing for interactions between funding amounts and business models, we measure a *negative* coefficient on the natural log of private equity funding. However, these results are significant only at the 10% level and are not robust to allowing for a step function in funding amounts. One might also be concerned that GBF was effective only for firms that had strong first mover advantages. To test if this is the case, in unreported regressions we interacted the natural log of the funding amount with the cohort dummies described in Table 3. There is no evidence that the influence of private equity funding is different for any of the three cohorts.

Several important qualifications are in order. Foremost, both the funding amount and the financing event are outcomes of a selection process whereby firms solicit funding from potential investors. This creates two problems. First, funding amounts are truncated from below by zero. Second, and much more seriously, financing itself is endogenous. If outside investors provide an added check on entrepreneurial decision making, then we should expect private equity financing to be an indicator of quality. Our ability to deal with this problem econometrically is limited, as we do not have separate quality indicators, or other instruments that might control for the endogeneity of funding decisions. However, we would expect quality to be positively correlated with the amount of funding, and hence this source of endogeneity should work against our central finding. Private equity investors commonly receive the right to liquidate a company in the event of a poor outcome. It is possible that the quality bias is washed out by earlier termination by private equity investors. While we cannot examine this possibility in our data, we note that Guler (2002) finds no evidence that VCs exit investment positions optimally.

In the regressions above our performance measure, survival, is perhaps not ideally suited for this task. VCs and entrepreneurs may have different success criteria: a lifestyle business might be successful in the eyes of the entrepreneur, but would not be a successful investment for a VC. If, after investment, a firm is viable as a lifestyle business but unlikely to provide a substantial cash-out opportunity for the investors, VCs might shut the business down for its salvage value. A similar non–VC-backed firm might choose to continue operations. Hence, while the performance of both firms is similar, the survival outcome would be different. To address this issue we calculate the internal rate of return (IRR) for ventures that pursued a GBF strategy. Empirically, we try to assess the IRR for firms that that received more than $3 million in private equity funding.[27] The sample contains 138 firms that received at least $3 million in funding, and together they received a total of $2.92 billion in funding. Of these 138 firms, 69 exited, 17 experienced liquidity events with a mean cash value of $72.6 million, and 52 remain ongoing private concerns. We investigated these liquidity events in an attempt to quantify the returns by examining press releases in Lexis-Nexis, using the Hoovers database and searching with Google. For every liquidity event, we multiplied the proceeds by 0.8, as a generous estimate of the share investors own. In ten cases, specific amounts were reported. For the other seven cases, we estimated the amounts under upper-bound assumptions that would magnify the IRR.[28] The IRR for the 69 exited firms together

[27]Ideally, we would measure IRR for both GBF and non-GBF firms. However, 59% of the firms in our sample report no funding. Without further information about in-kind contributions, it not possible to calculate IRR for these firms. As an alternative, we calculate the IRR for a set of GBF firms and compare it to estimated rates of the return for typical venture capital investments (Cochrane 2005).

[28]For example, in two cases, firms were purchased by public firms for undisclosed amounts. In order to comply with SEC regulations by filing form 8-K, public firms must disclose details of acquisitions if they are "material." Given, the lack of disclosure, we considered these acquisitions cash deals valued at $100 million,

with the 17 that experienced liquidity events was −44.5%. While it is not possible to value ongoing private concerns, we note that if each of the 52 such companies experienced liquidity events equal to the mean cash value of the 17 firms with successful exits, the IRR for the entire portfolio of firms pursuing GBF would be 11.1%. However, this result is likely optimistic given that the the bulk of investment in these firms occurred in 1999 and 2000 and the lack of current performance. By way of comparison Cochrane (2005) conservatively estimates mean arithmetic returns of 59% for a broad set of VC investments.[29]

As an alternative test of the merits of pursuing GBF—exploiting the fact that these firms are internet businesses—we measured their current web traffic rankings available via Alexa.com. If the VC-backed firms successfully executed a GBF strategy, then these surviving firms should have systematically higher traffic ratings than surviving non–VC-backed firms. If the GBF strategy were correct, and the criteria used to evaluate these businesses in the late 1990s were accurate, then web traffic measures would be an appropriate indicator of firm success.[30] Alexa reports that rankings below 100,000 are generally not statistically significant as they are based upon less than 1,000 daily hits in the general population, and much smaller numbers of hits in Alexa's sample. Of the 376 surviving firms, 61 (16%) have traffic rankings in the top 100,000 websites. Of these survivors, 71 are VC-backed, 14 of which (24%) have rankings in the top 100,000. Of the 308 non–VC-backed survivors, 47 (18%) have high ranking websites. We report these breakdowns in Table 7. There is little evidence to support the proposition that survival rates of VC-backed firms are held down because VCs enforce higher success thresholds. But this is a cautious conclusion for several reasons. First, the skewed nature of the success rates implies that there is little information from which to draw this conclusion. Second, it is possible that firms survived even though VCs liquidated their positions, in which case survival might indeed be a reasonable measure of success for our purposes. If large amounts of investment capital were irreversibly sunk,

under the assumption that acquisitions above this amount would certainly require public disclosure. In another case, a venture investment was made in a public firm and these shares were later offered in the public markets. We assumed that they were eventually sold at the peak stock price of $44 even though this price was transient and the stock is currently traded for less than $1.

[29]For the portfolio to generate typical venture returns of 27%, one of the portfolio companies would have had to generate a $10 billion return *for investors*, along the lines of Amazon, eBay, or Yahoo!.

[30]Alexa aggregates two measures, "reach" and "page views" to create its traffic rankings measure. "Reach" is the number of users who visit a particular website on a given day. The measure is usually expressed as a share. For example, if Yahoo has a reach of 0.28, then 28% of Alexa's sample of internet users visit Yahoo at least once per day. "Page views" is the total number of pages rendered by a website during a given period. This is a measure of use intensity. The ranking is based on the geometric means of reach and page rank, averaged over a three month period. Alexa samples web traffic behavior only of those that install an Alexa toolbar on their internet browser. While there is no way to know if this sample of several million internet users is representative of the population as a whole, there are several known biases. First, only Internet Explorer on Microsoft Windows is supported, thus the sample excludes users of other browsers and platforms. Second, traffic measures of Alexa.com and the internet archive (Archive.org) are known to be over-represented. Alexa also believes that the international representativeness of the sample is suspect. See http://pages.alexa.com/prod_serv/traffic_learn_more.html#traffic_rank for further details.

then, when poor results materialized, firms without capital to salvage may have been allowed to maintain operations. We would expect this to be the case for internet firms in particular. Third, due to the paucity of the data we pool the traffic ranking statistics across a diverse range of businesses, even though these rankings may not be strictly comparable.

In sum, the survival analysis shows that in our data private equity investment is not related to firm survival and this result is robust across many specifications. Moreover, we also find unremarkable IRR and no relationship between web traffic rankings and the receipt of VC funding. We interpret these results as consistent with the hypothesis that pursuing a GBF strategy was, on average, a poor strategy for most internet businesses during the late 1990s.

4 Discussion

The theoretical model describes conditions under which a belief cascade is likely, and the evidence in support of a GBF belief cascade appears strong. We provide evidence based upon an analysis of media content as well as statistical evidence based upon a sample of internet firms. Beliefs are inherently unobservable and our evidence is based upon a series of observations guided, in part, by our theoretical model. Extracting historical narrative from contemporary accounts is necessarily imprecise. That said, the basic fact pattern underlying the conditions identified in the model is compelling: the rise and fall of belief in GBF is the central narrative of the era.

The statistical evidence in support of the ex-post error of believing in GBF is based upon a survival analysis. Our central conclusions are driven by the lack of a significant statistical relationship between the pursuit of a GBF strategy, as measured by access to capital, and firm survival. A stronger result would have established a negative relationship between firm survival and entry size. However, if our hypothesis were wrong, there are many theoretical and empirical reasons to have expected a *positive* relationship. For example, if we observed firm quality, we would be able to account for endogenous variation in private equity funding, and systematically account for one such potential positive bias. Therefore, in light of the previous literature, our interpretation is reasonable. Moreover, we supplement our survival analysis with a calculation of the IRR of investments in firms that may have been pursuing a GBF strategy. Although tentative, the observed IRR is not supportive of the wisdom of pursuing GBF. A web traffic analysis leads to similar conclusions.

While we provide a significant body of evidence that a belief cascade on GBF occurred, the high survival rates are the only empirical evidence supporting the too-little-entry hypothesis. Moreover, interpreting differing survival rates across industries and time is an admittedly difficult task. Our support of the too-little-entry hypothesis is driven by this interpretation and the strong theoretical implications of a GBF belief cascade. At a minimum, the comparisons with other industries provide prima facie evidence that internet technology firms did not exit at higher than average rates, a result that would have obtained if low quality and excess entrants responded to the GBF hype. In an ideal study, we would provide systematic evidence of potential entrants choosing to forego entry after large first movers had signalled their intentions. Unfortunately, finding evidence of non-events is challenging.

5 Conclusion

We present four stylized facts about the Dot Com Era: (1) there was a widespread belief in a "Get Big Fast" (GBF) business strategy; (2) the increase and decrease in the size of venture capital deals was most prominent in the internet and information technology sectors and in the associated IPO and VC fundraising markets; (3) the survival rate of Dot Com firms is on par or higher than other emerging industries; and (4) firm survival is independent of private equity funding.

Individually, these stylized facts are consistent with various existing theories and empirical findings. For example, the private market gyrations are, in general, consistent with the recycling literature which predicts that strong public market performance would lead to higher valuations of internet firms in the private equity markets, an quicker time to IPO and increased entry into both the VC and internet industries. In addition, the propagation of GBF is consistent with research arguing that irrational exuberance drove investor behavior during the period. However, these literatures are inconsistent with new facts introduced in this paper: the high survival rates of Dot Com firms and the lack of correlation between survival and private equity funding. Future work may yet resolve these differences.

We offer a model that interprets the stylized facts in a framework of rational decision making under uncertainty. To this end, we extend the literature on herding and belief cascades by accommodating divergence between the information and incentives of venture capitalists and their investors. The model articulates conditions under which a belief cascade among venture capital decision makers can emerge, even if those beliefs are ex-post wrong. The model also shows how a secondary cascade can arise if investors and venture capitalists have access to different information about the nature of investment opportunities and how the supply of investment funds for venture capital can dry up if incentives are not aligned. The theory predicts observed venture capital patterns (Fact 2).

The model articulates conditions favorable to the emergence and persistence of a GBF belief cascade. In the paper, we provide historical evidence for the existence of the conditions and subsequent belief cascade (Fact 1). Such a cascade may have served as a perceived barrier to entry for potential entrepreneurs. Hence, an interesting implication of our theoretical exposition is that the survival rates of Dot Com firms should be relatively high (Fact 3) due to too little entry into individual markets. Furthermore, an incorrect belief in a GBF strategy suggests that the marginal value of an additional dollar of funding should be small. We find that marginal increases in private equity funding indeed did not increase the survival rates of internet firms (Fact 4). In addition, these detailed findings are corroborated by estimates of IRR and web traffic ratings.

To be clear, we do not posit that there was insufficient investment in internet ventures. Rather in the absence of a belief cascade, more entrants might have received smaller amounts of funding. To envision how these events might have unfolded, consider the case of Webvan, a $1 billion internet grocery venture that entered many major cities in 1999. Webvan turned out to be a spectacular failure. Absent beliefs about the necessity of GBF, we might have observed many smaller-scale startups all experimenting with different models—perhaps in different cities—to deliver grocery products to the consumer. Instead, we observed a single very large bet on one particular delivery model. In general, mistaken belief in GBF concentrated too many resources in too few ventures. In this sense, we argue, there was too little entry.

Finally, we also suggest that it is unlikely that such large bets would have been undertaken if conditions under which academic theories of increasing returns to scale and preemption had been more accurately and thoroughly represented in the popular press. If they had, investors may have more accurately assessed the applicability of these theories. Theory matters for practice, and if misinterpreted, adversely so.

A Theoretical Appendix

A.1 The model

States of the world There are three states of the world that parameterize the distribution underlying the opportunities for venture capital investments, represented by $\omega \in \{L, S, B\}$. The state of the world is never observed.

Opportunities In each period, an opportunity of type $\alpha \in \{L, S, B\}$ is drawn independently from the distribution associated with the true state of the world. The type is correlated with the state of the world. The type of an opportunity is never directly observed.

Signals In each period, after an opportunity of type α is drawn, the particular VC whose turn it is to invest in the opportunity observes a private signal, $\sigma \in \{L, S, B\}$, which is correlated with the type of the opportunity. This signal is never observed by anyone other than this particular VC, and there are no means for the VC to ever reveal it.

Projects After observing a signal about its opportunity, the VC has the opportunity to invest in a project $a \in \{L, S, B\}$, if it has received funds from investors. Each type of project has a fixed cost of 1 in the period in which it is started, and is costless thereafter. Each project takes T_2 periods to mature, upon which time its profits are realized.

In a market of type α, it is optimal to invest in a project of type $a = \alpha$, where $a = L$ corresponds to "large-scale" entry, $a = S$ corresponds to "small-scale" entry, and $a = B$ corresponds to buying risk-free bonds rather than entering.[31] In particular, regardless of α, a project of type $a = B$ always succeeds, yielding gross revenue of $1 + \pi_B$. On the other hand, a project of type $a = L$ or $a = S$ (an "entry" project) yields success if and only if the type of project matches the nature of the opportunity, i.e., $a = \alpha$. When a project of type a succeeds, it yields gross revenue of $1 + \pi_a$. When an entry project fails, it yields gross revenue of zero; i.e., the initial investment is lost.

The profitability of a project is revealed at two dates. First, T_1 periods after it is initiated, the entire population of VCs observes whether it will succeed or not. However, investors do not observe its success or failure until profits are realized, $T_2 > T_1$ periods after the project is initiated. There are no means for the VCs to ever reveal the profitability of a project to investors before the profits are realized.

Venture capitalists and investors There are a countably infinite number of different risk-neutral VCs, each associated with a particular time period and a particular investment opportunity. There is a continuum of infinitely lived risk-neutral investors, with total mass of 1, each of whom has an endowment of 1 per period which she can use either to fund a VC or to invest directly in risk-free bonds to earn gross revenues of $1 + \pi_B$ without paying a percentage of profits to a VC.

Timing and payoffs In each period $t = 1, \ldots, \infty$, first VCs observe whether the project initiated in period $t - T_1$ (if any) is going to succeed or fail; at the same time, the project initiated in period $t - T_2$ (if any) reaches maturity and its profits are realized and distributed to VCs and investors. The VC responsible for the project earns a fraction $\varepsilon \in (0, 1)$ of net returns; that is, $\varepsilon\pi_a$ in the case of a successful entry project, 0 in the case of a failed entry project, and $\varepsilon\pi_B$ in the case of bonds.

Second, investors first decide whether to put their money in venture capital or in risk-free bonds. If they choose venture capital, then VC_t can invest in the opportunity that arises in that period. After receiving funding, VC_t observes a private, noisy signal $\sigma_t \in \{L, S, B\}$ that is correlated with α_t. Then VC_t chooses which type of project to invest in, $a_t \in \{L, S, B\}$. All other VCs observe VC_t's project type, while investors observe only whether VC_t invested in entry ($a_t \in \{L, S\}$) or in bonds ($a_t = B$).

Distributions All players have common knowledge of their common beliefs about the distributions of α conditional on ω, and of σ conditional on α. Conditional on ω, all draws of α are serially independent. Conditional on α_t, σ_t is independent of ω, and all draws of σ are serially independent. The players have common knowledge of their common prior belief μ_1 about the state of the world at the outset of the game.

[31] "Bonds" represent the idea that investors' best outside opportunity is less risky than venture capital.

Interpreting the model As noted in Section 2.1, a more accurate depiction of the venture capital market would include the limited partners (LPs), and give them an information set similar to that of the VCs. In interpreting the model presented here, we think of a VC in the model as representing the union of an actual VC with its small number of associated LPs. This interpretation can be supported by an assumption that when a VC and its LPs make their initial investment in a project, they already know all the information that individual investors will know at the time the project reaches IPO, and that the IPO occurs immediately before the success or failure of the project becomes known (after T_2 periods). Furthermore, assume that in the IPO, individual investors buy all the shares from the VC and the LPs, at a price that exactly offsets the initial investment, while the VC and the LPs retain an option to buy back an ε share of the project at a strike price of 1 with an exercise date that occurs after T_2 periods. These assumptions would imply that the individual investors participating in the IPO will behave exactly as the investors in the model, and that the VC and LPs together will behave exactly as the VC in the model.

Unfortunately, these assumptions are highly unrealistic since the investors, prior to participating in the IPO for project a_t, should naturally be able to observe the success or failure of other projects that preceded a_t. In our view, this is the main weakness of the model. However, allowing the investors to view new information prior to the IPO for project a_t that was not known to VC_t in period t would allow investors to update their beliefs about VC_t's investment strategy at time t. Knowing this, to form its investment strategy VC_t would need to predict the investors' beliefs at time $t + T_2$, given its beliefs about what new information would then be revealed between times t and T_2. Such a model might be amenable to numerical computation or Monte Carlo simulation, but it would not lend itself to analytical results.

For this reason, we believe this simplification is necessary. We also conjecture that the qualitative nature of our results would carry over to a more realistic setting, since the beliefs of the investors at time t in the model can be viewed as representing the VC's and LPs' reduced form estimate of what individual investors are likely to believe at the time of the IPO.

A.2 Analysis

VCs' beliefs Let μ_t be the common belief of the VCs at the start of period t, where μ_1 is the common prior. Let $\hat{\mu}_t$ be the common belief of the VCs in period t after the success or failure of the period $t - T_1$ project has been revealed. Let $\phi_t(\cdot|\sigma_t)$ be VC_t's posterior belief about his own opportunity, updated from $\hat{\mu}_t$ after observing σ_t; then

$$\phi_t(\alpha_t|\sigma_t) = \frac{\sum_\omega \Pr(\sigma_t|\alpha_t) \Pr(\alpha_t|\omega)\hat{\mu}_t(\omega)}{\sum_\omega \sum_\alpha \Pr(\sigma_t|\alpha) \Pr(\alpha_t|\omega)\hat{\mu}_t(\omega)}. \tag{4}$$

Before any new information about the success or failure of past projects is revealed, the updating rule for μ_{t+1} from $\hat{\mu}_t$ depends only on a_t:

$$\mu_{t+1}(\omega^*|a_t) = \frac{\sum_\alpha \sum_\sigma \Pr(a_t|\sigma) \Pr(\sigma|\alpha) \Pr(\alpha|\omega^*)\hat{\mu}_t(\omega^*)}{\sum_\omega \sum_\alpha \sum_\sigma \Pr(a_t|\sigma) \Pr(\sigma|\alpha) \Pr(\alpha|\omega)\hat{\mu}_t(\omega)}. \tag{5}$$

Note that $\Pr(a_t|\sigma)$ is an expression of VC_t's investment strategy.

If there was a project initiated in period $t - T_1$, then its success or failure (denoted γ_{t-T_1}) becomes known to the VCs. Hence the updating rule for $\hat{\mu}_t$ is

$$\hat{\mu}_t(\omega^*|\gamma_{t-T_1}) = \frac{\sum_\alpha \Pr(\gamma_{t-T_1}|a_{t-T_1}, \alpha) \Pr(\alpha|\omega^*)\mu_t(\omega^*)}{\sum_\omega \sum_\alpha \Pr(\gamma_{t-T_1}|a_{t-T_1}, \alpha) \Pr(\alpha|\omega)\mu_t(\omega)}. \tag{6}$$

Investors' beliefs In order to determine whether to invest in venture capital or in bonds, investors must estimate their expected returns, taking into account the investment strategies of the VCs. To do so, the investors must use the events they have observed to compute their posterior distribution over VC beliefs. Hence investors must maintain beliefs over both the state of the world ω and the VCs' beliefs μ. We will not write down the updating rules for these beliefs explicitly; instead we will make arguments about the directions and magnitudes of these updates to prove some of our results, and simulate them to demonstrate other results.

Decisions The problem of a VC in period t is to choose $a_t \in \{L, S, B\}$ to solve

$$\max_{a_t} \begin{cases} \varepsilon\pi_L\phi_t(\alpha_t = L|\sigma_t) & \text{if } a_t = L, \\ \varepsilon\pi_S\phi_t(\alpha_t = S|\sigma_t) & \text{if } a_t = S, \\ \varepsilon\pi_B & \text{if } a_t = B. \end{cases} \tag{7}$$

The problem of an investor in period t is to choose to invest in venture capital if

$$\mathbb{E}_{\hat{\mu}_t}\left[\begin{array}{c} \big(1 + (1-\varepsilon)\pi_L\big) \Pr(a_t = L|\phi_t)\phi_t(\alpha_t = L|\sigma_t) \\ + \big(1 + (1-\varepsilon)\pi_S\big) \Pr(a_t = S|\phi_t)\phi_t(\alpha_t = S|\sigma_t) \\ + \big(1 + (1-\varepsilon)\pi_B\big) \Pr(a_t = B|\phi_t) \end{array}\right] \geq 1 + \pi_B, \tag{8}$$

where expectations are taken over investors' beliefs about $\hat{\mu}_t$, and $\Pr(a_t|\phi_t)$ expresses VC$_t$'s investment strategy; otherwise the investor should invest in bonds directly.

A.3 Results

We maintain the following three assumptions on the parameters.

Assumption 1 (Informativeness)**.** $\Pr(\alpha = \omega|\omega) > \Pr(\alpha = \hat{\omega}|\omega)$ *for all* $\hat{\omega} \neq \omega$, *and* $\Pr(\sigma = \alpha|\alpha) > \Pr(\sigma = \hat{\alpha}|\alpha)$ *for all* $\hat{\alpha} \neq \alpha$.

Assumption 2 (Relevance)**.** *The parameters are such that investors strictly prefer to invest in venture capital given* μ_1*; i.e., Eq. 8 is satisfied for* $t = 1$.

Assumption 3 (Richness)**.** *There exists* $\eta > 0$ *such that, for all* $\omega \in \{L, S, B\}$*, if* $\mu_t(\omega) < \eta$ *then VC*$_t$ *chooses* $a_t \neq \omega$ *regardless of* σ_t.

Example. *An example of a parameter set that satisfies these assumptions is* $\pi_B = 3$, $\pi_S = \pi_L = 10$, *and* $\varepsilon = \frac{2}{9}$; $\Pr(\alpha = \omega|\omega) = \frac{2}{3}$ *with* $\Pr(\alpha = \hat{\omega}|\omega) = \frac{1}{6}$ *for all* $\hat{\omega} \neq \omega$; *and* $\Pr(\sigma = \alpha|\alpha) = \frac{1}{2}$ *with* $\Pr(\sigma = \hat{\alpha}|\alpha) = \frac{1}{4}$ *for all* $\hat{\alpha} \neq \alpha$. *Additionally, let* $\mu_1(L) = \frac{1}{2}$ *and* $\mu_1(S) = \mu_1(B) = \frac{1}{4}$.

We will explore the consequences of the following results in the context of this example.

Definition 1. An A *cascade* occurs in period t, for $A \in \{L, S, B\}$, when either (i) $\Pr(a_t = A|\sigma_t) = 1$ regardless of σ_t; or (ii) if no information about the period $t - T_1$ project were revealed, then the condition in (i) would hold.

That is, a cascade occurs in period t if VC$_t$ ignores its private signal, or would do so if it did not learn the outcome of the period $t - T_1$ project. For convenience, as we consider a particular series of realizations, we will call the first cascade to occur a *primary* cascade, and the second one a *secondary* cascade.

Proposition 1. *If T_1 is sufficiently high then a primary L cascade can occur, which lasts (at least) until $t = T_1 - 1$.*

Proof. Consider a string of private signal realizations $\sigma_1, \ldots, \sigma_{n_1} = L, \ldots, L$. At the start, the first $n_1 \geq 1$ VCs choose their investment projects to match their own private signals, $a_t = \sigma_t$. So when the other VCs observe that $a_t = L$, they infer that $\sigma_t = L$, and update their beliefs as follows:

$$\mu_{t+1}(\omega = L) = \frac{\big(\Pr(\sigma = L|\omega = L)\big)^t \mu_1(\omega = L)}{\sum_\omega \big(\Pr(\sigma = L|\omega)\big)^t \mu_1(\omega)}. \tag{9}$$

Since this expression approaches 1 as the string of realizations of L signals goes to infinity, after some initial period eventually one of the following will be satisfied:

$$\pi_L \phi_t(\alpha_t = L|\sigma_t = S) > \pi_S \phi_t(\alpha_t = S|\sigma_t = S), \tag{10}$$
$$\pi_L \phi_t(\alpha_t = L|\sigma_t = B) > \pi_B. \tag{11}$$

The first condition implies that VC$_t$ will choose $a_t = L$ even if $\sigma_t = S$; the second condition implies that VC$_t$ will choose $a_t = L$ even if $\sigma_t = B$. If only one of these conditions is satisfied at first, then subsequent VCs will invest more coarsely, but are still more likely to choose $a_t = L$ when $\sigma_t = L$ than otherwise (by Assumption 3), and hence VC beliefs continue to update to favor state $\omega = L$ as long as the string of realizations of L continues. Hence, eventually, after a long enough string of realizations of $\sigma = L$, both conditions will be satisfied and VCs will cease updating their beliefs. Let n_1 be the length of this string of realizations. After n_1 periods, a primary L cascade begins, as each additional VC will now invest $a = L$ regardless of σ.

Choose $T_1 \geq n_1$, so that no information about the success or failure of any projects is revealed until after a primary L cascade may have started. Then the probability of a primary L cascade is at least $\big(\min_\omega \Pr(\sigma = L|\omega)\big)^{n_1}$.

Note that investors, if they initially were willing to invest in venture capital, update to increase their belief that such investments may be profitable, because they have observed that all VCs have invested in entry projects. They are aware that a cascade may occur, but they must also consider the possibility of strings of realizations that do not induce cascades and yet still result in entry in every period, all of which lead them to (weakly) reduce their belief in $\omega = B$. Hence they continue to update to favor investment in venture capital even if a primary L cascade is occurring. □

Example (Continued)**.** *For this parameter set, a primary L cascade begins in period 6, after $n_1 = 5$ realizations of $\sigma = L$, assuming $T_1 \geq 5$. For the example, let $T_1 = 6$.*

The timeline for this example (which continues through period 17 to illustrate further events described below) is shown in Figure 4. The VCs' beliefs are plotted in Figure 1. As each successive VC invests in an L project, later VCs update their beliefs in favor of a high probability of L projects, until their beliefs reach the L cascade region. During this time, the investors observe that VCs continue to invest in entry projects, leading them to update their beliefs in favor of investing in venture capital. This is illustrated in the bottom section of Figure 4, where investors' expected profits (mostly) rise for the first 7 periods. Investors' expected profits are computed for the example by Monte Carlo simulation, as described below.

Proposition 2. *Suppose that T_1 is sufficiently high that a primary L cascade can occur. Then, if $T_2 - T_1$ is sufficiently high, a secondary S cascade can occur.*

Proof. Consider a string of realizations $\alpha_1, \ldots, \alpha_{T_1} = S, \ldots, S$, even while $\sigma_1, \ldots, \sigma_{T_1} = L, \ldots, L$, and let T_1 be large enough that a primary L cascade occurs. Then in each period $t \in \{T_1+1, \ldots, T_2\}$, VCs observe that the project started in period $t - T_1$ is going to fail. From this, they infer perfectly that $\alpha_{t-T_1} \in \{S, B\}$, and they revise their belief in $\omega = L$ downward. In that same period, VC_t observes σ_t, but even if $\sigma_t = L$ and VC_t invests in $a_t = L$, the overall effect on μ is for the VCs to revise their belief in state $\omega = L$ downward, since upgrading the period $t - T_1$ observation from $\sigma_{t-T_1} = L$ to $\alpha_{t-T_1} = S$ is stronger evidence against $\omega = L$ than observing $\sigma_t = L$ is evidence in favor of $\omega = L$.

Hence the primary L cascade will end after enough project failures of type L are observed. Then, by the same reasoning as in Proposition 1, a string of realizations $\sigma_{T_1+1}, \ldots, \sigma_{T_1+n_2} = S, \ldots, S$, with n_2 sufficiently large, will generate a secondary S cascade.

Choose $T_2 \geq T_1 + n_2$ so that no information about the success or failure of any projects is revealed to investors until after a secondary S cascade has begun. Then, conditional on the realizations specified for $t = 1, \ldots, T_1$, the probability of a secondary S cascade is at least $\left(\min_\omega \Pr(\sigma = S|\omega)\right)^{n_2}$.

Investors in this environment observe only that VCs are continuing to invest in entry; they do not observe whether projects are large or small, or that projects are failing. So although they are aware that projects may be failing and that VCs may be cascading on $a = S$ even when it is not in the investors' interests, the investors still continue to update to favor investment in venture capital because they have not observed any information that would weigh against the desirability of investing in venture capital. □

Example (Continued)**.** *For this parameter set, starting from a primary L cascade in period 7, a secondary S cascade begins in period 10, after VCs collectively observe 4 consecutive failures of type L projects, and the individual VCs investing in the first 3 of these periods receive signals $\sigma = S$, assuming that investors continue to provide funds to the VCs through period 9. For the example, let $T_2 = 7$.*

The VCs' beliefs leading up to the secondary S cascade in this example are illustrated in Figure 2, where, starting from a primary L cascade, the failure of the first L project knocks their beliefs out of the L cascade region. This allows the next VC to invest in an S project if it receives an S signal. Combining several consecutive failures with several consecutive S signals brings VCs' beliefs to the S cascade region in period 10. Figure 4 illustrates that in period 7, when investors know that VCs will have observed the success or failure of the period 1 project, the investors' expected profit from investing in venture capital jumps significantly, since investors understand that VCs will take this new information into account. Starting in period 8, however, investors gradually learn that the early L projects are failing. This reduces their expected profit from investing in venture capital, leading to the following result. (We do not call it a proposition because it holds only for a restricted set of parameters.)

Result 3. *There exists a non-empty, open set of parameters such that, following the end of a primary L cascade and the start of a secondary S cascade, investors stop funding venture capital and switch to investing directly in bonds.*

Sketch of proof. The example considered in this section displays the properties in the result, as shown below, proving that the set of such parameters is non-empty. The continuity properties of the model assure there exists an open neighborhood of the example parameters, such that all parameters in the neighborhood display these properties as well. □

The intuition behind the result is as follows: Because VC$_t$ earns a portion ε of the period t project's net returns while investors earn the project's gross revenues minus their initial investment and the VC's portion, their incentives to invest are not aligned. Hence there exist values of $\hat{\mu}_t$ for which VC$_t$ would prefer to choose $a_t = S$ but investors—if they knew $\hat{\mu}_t$—would prefer to invest directly in risk-free bonds rather than provide funds to the VC. Instead, their beliefs about $\hat{\mu}_t$ are based on their common prior μ_1 and updated based on the information they have observed. That is, the investors know what beliefs VC$_t$ would hold for each possible realization of the information that VC$_t$ could have observed that is consistent with the (coarser) information that the investors themselves have observed, and they know what VC$_t$'s investment strategy would be for each of these possible beliefs. Investors compute their overall expected profit from investing with VC$_t$ by adding up their expected profits from investing for each realization of information that VC$_t$ could have observed, weighted by the probabilities of these realizations given their prior beliefs about the underlying state of the world. If they put enough probability weight on realizations that yield values of $\hat{\mu}_t$ for which they would prefer to invest directly in risk-free bonds, then their expected payoff from investing with VC$_t$ will be negative.

Finally, the larger is ε, the wider the range of VC beliefs $\hat{\mu}_t$ for which investors would prefer to invest directly in risk-free bonds. For instance, if $\varepsilon = 1$, then investors will prefer to invest directly in risk-free bonds regardless of $\hat{\mu}_t$. The difficulty in proving the result analytically arises from the need to identify a value of ε that is consistent with the occurrence of a primary L cascade and a secondary S cascade, and which leads investors to invest directly in bonds.

Although we are unable to prove analytically that this property is generally satisfied, we demonstrate by Monte Carlo simulation that it holds for the example. The simulation process works by randomly generating first the state of the world ω and then sequences of projects $\alpha_1, \alpha_2, \ldots$ and signals $\sigma_1, \sigma_2, \ldots$, computing the VCs' beliefs and actions given these sequences, and discarding those that lead to investments and outcomes that are inconsistent with the coarse information sets of the investors. The investors' beliefs must be simulated separately for each period $t = 2, 3, \ldots$, because some sequences that are consistent with investors' first t periods of observations are rendered inconsistent with investors' period $t+1$ observations. To generate the data in Figure 4, we simulated at least 2000 consistent sequences for each period, including 5000 consistent sequences each for periods 10–14. As the number of periods increases, the computational burden increases exponentially because fewer sequences are consistent.

Example (Continued)**.** *For this parameter set, if during periods 1–10 VCs never invest in bonds and the projects from periods 1–4 all fail, then starting in period 8 investors begin to observe that the projects from periods 1–4 have failed. In periods 8–10 their expected value of investing in venture capital remains positive (including the opportunity cost of investing in bonds directly), but in period 11 their expected value becomes negative, at approximately $-.054$. Hence in period 11 they invest in bonds directly rather than fund VC_{11}.*

This scenario is consistent with a primary L cascade that starts in period 6, and a secondary S cascade that starts in period 10, as previously established.

Figure 4 illustrates the decline in investors' expected profits that occurs once the early failures become public. Even after they switch to investing in bonds directly (in period 11), their expected profits continue to decline as additional failures become public. The trend reverses, however, when the first S project (from period 7) publicly succeeds in period 14, leading to the following result.

Result 4. *There exists a non-empty, open set of parameters such that, following the end of a primary L cascade and the start of a secondary S cascade, investors first stop investing in venture capital and switch to bonds, but later invest back into venture capital.*

Intuition. Suppose that the events of 3 have come to bear, and investors have withheld their funds from venture capital to invest in bonds directly. We already have that $\sigma_{T_1}, \ldots, \sigma_{T_2} = S, \ldots, S$; let $\alpha_{T_1}, \ldots, \alpha_{T_2} = S, \ldots, S$ as well. Then, beginning in period $T_1 + T_2$, investors observe whether the project from period $t - T_2 \geq T_1$ is successful. Since VCs started a secondary S cascade at some point between T_1 and T_2, investors eventually observe a string of successful projects, and this will lead them to revise their belief in state $\omega = B$ downward. Once this belief is sufficiently favorable, they will decide to invest in venture capital once again.

The difficulty in proving the result analytically is to ensure that the situation described in the previous paragraph is consistent with a situation in which investors have switched to investing directly in bonds. That is, we have shown that investors may switch to bonds when T_2 is relatively small, but now we need this also to be the case for T_2 large enough that a sufficiently large string of successful small projects is actually undertaken. Although we are unable to prove the result analytically, we demonstrate by Monte Carlo simulation that it holds for the example, below. As with the previous result, the properties hold for an open neighborhood of the example parameters by continuity. □

Example (Continued)**.** *For this parameter set, if during periods 1–10 VCs never invest in bonds, the projects from periods 1–6 all fail and the projects from periods 7–10 all succeed, then (as previously established) investors withhold funds from venture capital in period 11. In periods 11–13, they* *continue to observe project failures, and their expected value of investing in venture capital continues to decrease. But in period 14 they observe the success of the period 7 project, after which their expected value turns positive, at approximately 0.220 (based on 5000 Monte Carlo trials). Hence in period 14 they provide investment funds for VC_{14}.*

This scenario is consistent with a primary L cascade that starts in period 6, and a secondary S cascade that starts in period 10, as previously established.

As Figure 4 illustrates, when investors return their funds in period 14, the VCs immediately revive their S cascade. This is because in periods 11–14 they observe no new information other than the outcomes of the projects started in periods 5–8, which serve only to reinforce the S cascade. Figure 4 shows what might happen if the project from period 10 succeeds, such that the S cascade continues at least through period 17 (and, indeed, through period 20, since no projects were undertaken in periods 11–13). Propositions 1–2 and Results 3–4 are also consistent with scenarios in which the period 10 project fails, but these scenarios were excluded from our Monte Carlo trials for period 17.

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Table 1: Kaplan-Meier Exit Rates

Time is recorded from year of entry. All data is considered left censored by the minimum of 1998 or year of entry. Hazard rates are Kaplan-Meier hazard function calculations. *Beginning total* is the number of firms at risk at beginning of period. *Exits* is the number of exiting firms of corresponding vintage. *Net lost* is the adjustment at the end of period between newly observed firms (i.e., no longer left-censored) net of exits. Hence, in the first row a net of −52 represents 20 exits of first year entrants minus 72 firms first observed in their second year. "Exit rate" is the annual exit rate of observed firms, conditional on survival to the beginning of that period. *Cumulative hazard function* is the Kaplan-Meier cumulative exit rate that adjusts for both right and left censoring. Standard errors refer to the cumulative exit rate. Statistics for firms after year 6 are subject to severe right-censoring and should be heavily discounted.

Age	Beginning total	Exits	Net lost	Exit rate	Cumulative hazard function	Std. error	[95% conf. int.]	
1	681	20	−52	0.03	0.03	0.01	0.02	0.05
2	713	88	−48	0.12	0.15	0.01	0.13	0.18
3	673	83	4	0.12	0.25	0.02	0.22	0.29
4	586	90	47	0.15	0.37	0.02	0.34	0.40
5	449	73	80	0.16	0.47	0.02	0.44	0.51
6	296	35	108	0.12	0.53	0.02	0.50	0.57
7	153	11	65	0.07	0.57	0.02	0.53	0.61
8	77	5	30	0.06	0.60	0.02	0.55	0.64
9	42	6	30	0.14	0.65	0.03	0.60	0.71
10	6	1	2	0.17	0.71	0.06	0.60	0.82
12	3	0	2	0.00	0.71	0.06	0.60	0.82
14	1	0	1	0.00	0.71	0.06	0.60	0.82

Table 2: Exit by year of entry

Cumulative hazard rates by year-entry cohort. The number of firms in each cohort are reported in parentheticals below the year of entry. Firms that entered before or during 1996 are grouped (includes 1 entrant from 1996, 2 from 1993, 1 from 1994, 3 from 1995, and 47 from 1996). *Cumulative exit rate* is the weighted mean of the exit rates for each cohort and represents the cumulative exit rate of firms in the sample in various years. *Total at period start* is the total number of firms in operation during the year. *Exits* is the number of firms that ceased operating during that year. *Exit rate* is the corresponding quotient. The bottom row reports (from left to right) total firms competing in the sample, total exits, and the average exit rate (unweighted average, 2000 and 2004).

	Year of entry									
Year of exit	≤1996 (54)	1997 (52)	1998 (113)	1999 (217)	2000 (231)	2001 (109)	Cumulative exit rate (mean)	Total at period start	Exits	Exit rate
1998	0	0	0					219	1	0.00
1999	0.00	0.00	0.02	0.00			0.00	433	3	0.01
2000	0.04	0.02	0.07	0.12	0.03		0.06	622	42	0.06
2001	0.13	0.19	0.21	0.25	0.22	0.09	0.20	619	112	0.15
2002	0.19	0.37	0.30	0.36	0.35	0.25	0.32	536	93	0.15
2003	0.24	0.38	0.35	0.43	0.48	0.39	0.41	467	70	0.13
2004	0.35	0.42	0.42	0.50	0.65	0.56	0.52	376	91	0.19
							Total:	788	412	0.14

Table 3: Descriptive Statistics

Descriptive statistics for 788 firms formed to exploit the emergence of the internet, measured at the last year of observation. Means, standard deviations, minima and maxima are reported. Survival indicates that either the firm survived as a separate entity through the end of 2004 or was acquired. Financing data were collected by matching firms in our sample to the Thompson Financial Venture Economics database and extracting financing information reported in firms' business planning documents (Goldfarb et al. 2005). *Ln private equity funding* is the logarithm of all private equity financing received measured in thousands of dollars (log(0) is set to 0). The dummy variables *Venture financing* and *Private equity* flag firms that received venture financing or private equity, respectively. *Unobserved VC funding amount* and *Unobserved PE funding amount* are dummy variables indicating whether we observed that funding was received, but not the amount. The revenue model dummy variables indicate whether the firm reported those types of revenue models in its business planning documents (see Table 5). The categories are not mutually exclusive.

Variable	Mean	Std. Dev.	Min	Max
Survived	0.47	0.50	0	1
Financing Variable				
Ln private equity funding	3.09	4.00	0	12.48
Dummy: Venture financing	0.14	0.35	0	1
Dummy: Private equity	0.41	0.49	0	1
Unobserved VC funding amount	0.01	0.13	0	1
Unobserved PE funding amount	0.03	0.17	0	1
Revenue Models				
Advertising	0.36	0.48	0	1
Subscriptions	0.25	0.43	0	1
Markup	0.18	0.39	0	1
Production	0.26	0.44	0	1
Referral	0.13	0.33	0	1
Fee for Service	0.62	0.49	0	1
Commission	0.23	0.42	0	1
Number of Revenue Models	2.03	1.03	1	6
Cohorts				
Founded before 1997	0.07	0.25	0	1
Founded 1997–1999	0.48	0.50	0	1
Founded 2000–2002	0.45	0.50	0	1
Exited after 1999	0.94	0.23	0	1

Table 4: Unconditional Survival Rates by Category

Unconditional survival rates by total funding percentiles. Survival indicates that either the firm survived as a separate entity through the end of 2004 or was acquired. The minimum and maximum of each percentile group is reported beneath the column label. Financing data are collected by matching firms in our sample to the Thompson Financial Venture Economics database and extracting financing information reported in firms' business planning documents (see Goldfarb et al. 2005). Firms that did not receive any private equity funding (59% of the sample) are grouped together. Four additional percentile groups are reported.

Variable*	Exited	Survived	Total	Survival Rate
Total Funding Percentiles				
Below 59th (no funding)	254	224	478	0.47
59th to 74th ($8200–$1.1M)	65	45	110	0.41
75th to 89th ($1.2M–$9.2M	69	52	121	0.43
90th to 94th ($9.4M–$25M)	20	19	39	0.49
95th to 99th ($25.2M–$263.7M)	13	27	40	0.67
Financing Status				
Venture-backed	54	59	113	0.52
Private equity–backed	180	145	325	0.45

* Descriptive statistics for 788 firms, measured at the last year of observation.

Table 5: Revenue Models

Revenue models are extracted from firms' business planning documents. The categorization follows Afuah and Tucci (2003). A brief description of each model type and a few of sample firms who pursued these models are given. The categories are not mutually exclusive; the mean number of revenue models a firm pursues is 2. The most common revenue model listed was fee for service (62%), followed by advertising (36%), production (26%), subscription (25%), commission (23%), markup (18%), and finally referrals (13%). Note: Firms classified exclusively as "Other" were dropped from the analysis.

Revenue Model Explanation:		**Examples**
Commission-based	A fee that is imposed on a transaction by a third party (usually an intermediary).	Insta-cash International Unibarter.com
Fee-for-Service	Pay as you go option, charged for professional service as you use it.	Metalogics, Inc. Flash Gordon
Advertising	Business of attracting public attention to a good or service, achieved through banner ads, pop ups, permanent buttons, etc.	RealTraveling.com Fidget
Subscription	Company charges a flat rate to use a service for a certain period of time	Tendersys.com Homesmart.com
Referral	Fees for steering customers to another company, can either be a flat fee or a fee per click-through	E-sitings Insureconnection
Production	Manufacturer sells directly over the Internet, cuts out middleman	Games Interactive 100x.com
Mark-up Based	The Middleman, business not in production but in resale	RealLegends.com Smartenergy
Other	Either not enough information to classify, or the revenue model was outside the scheme of an Internet business	Avatar Project

Table 6: Hazard Regressions

The dependent variable is exit in year t. Hazard ratios were estimated using a proportional, piecewise baseline hazard model as in Equation 1, where separate baseline hazard rates are estimated for each firm age measured in years. A total of eight baseline hazards were estimated. This semiparametric method does not impose structure on the baseline hazard. *Dummy: Venture financing* flags firms that received venture capital, and *Dummy: Private equity* flags firms that received private equity financing prior to year t. *Ln private equity funding* is the natural log of private equity financing (in thousands of dollars) received through year t (where ln(0) is set to 0), and *Dummy: Zero private equity* flags firms that did not receive private equity prior to year t. *Ln venture capital received* is the natural log of venture capital (in millions of dollars) received through year t, and *Dummy: Zero venture capital* flags firms that did not receive VC financing prior to year t. Inclusion of controls for revenue model, cohort, exit after 1999, and missing PE/VX dummies are reported in the bottom three rows. *Missing PE/VX dummies* indicate whether we observed that funding was received, but not the amount. A step function is estimated in Model (e) to evaluate the robustness of the lack of statistical association between the amount of financing and survival to the natural log specification.

	a	b	c	d	e	f
Dummy: venture financing		0.77		0.872	0.956	0.861
		(1.21)		(0.71)	(0.25)	(0.93)
Dummy: private equity						1.220+
						(1.91)
Ln private equity funding	1.019	0.979	1.037	0.956		
	(0.56)	(0.39)	(0.71)	(0.91)		
Dummy: Zero private equity	0.776	0.971	1.088	0.622		
	(0.84)	(0.09)	(0.23)	(1.36)		
Ln venture capital received			0.965			
			(1.49)			
Dummy: Zero venture capital			1.061			
			(0.23)			
Dummy: Percentiles 59-74					1.204	
					(1.42)	
Dummy: Percentiles 75-89					1.193	
					(1.21)	
Dummy: Percentiles 90-94					0.986	
					(0.06)	
Dummy: Percentiles 95-99					0.682	
					(1.16)	
Revenue Model Controls	Yes	Yes	Yes			Yes
Cohort and Post-March 2000 Dummies	Yes	Yes	Yes			Yes
Missing PE/VX Dummies	Yes	Yes	Yes			

Robust z statistics in parentheses, 3684 firm-years, Hazard ratios reported.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 7: Traffic Rankings

Web traffic rankings for websites are reported for venture and non-venture firms. The data are from Alexa.Com (Alexa). Alexa aggregates two measures, "reach" and "page views" to create its traffic rankings measure. "Reach" is the fraction of users who visit a particular website on a given day. "Page views" is the total number of pages rendered by a website during a given period. This is a measure of use intensity. The ranking is based on the geometric means of reach and page views, averaged over a three month period. Alexa samples web traffic behavior only of those that install an Alexa toolbar on their internet browser, a population of several million internet users. See http://pages.alexa.com/prod_serv/traffic_learn_more.html#traffic_rank for details on potential biases in Alexa.com's measures. Alexa reports that rankings below 100,000 are generally not statistically significant as they are based upon less than 1,000 daily hits in the general population, and much smaller numbers of hits in Alexa's sample.

Number of firms in traffic ranking percentile groups			
Percentile	Non-Venture Firms	Venture Firms	Alexa Ranking
1–5	15	6	1–16,078
6–10	17	4	16,079–42,626
11–15	15	6	42,627–100,000
15–99	261	57	>100,000

Figure 1: Primary Cascade (from the Example in the Appendix)

The triangle depicts the simplex of VCs' beliefs about the state of the world. A belief is expressed as a vector $\big(\mu(\omega = L), \mu(\omega = S), \mu(\omega = B)\big) \in \mathbb{R}^3$, which must satisfy $\mu(\omega = L) + \mu(\omega = S) + \mu(\omega = B) = 1$. Thus the set of possible beliefs lies in triangular subset of a plane in $\mathbb{R}^3$—a "simplex". To visualize beliefs in two dimensions, we show only the simplex. The extreme points represent degenerate beliefs that assign probability 1 to one of the three states of the world. Points on the side boundaries represent beliefs that assign positive probability to only two states of the world. Points on the interior assign positive probability to all three states, and assign greater weight to states for which the degenerate beliefs are closer.

Each region of the simplex is labeled according to the types of investments that VCs may choose when their beliefs fall in that region. The point μ_1 represents the prior beliefs of the example and is in the region labeled $\{L, S\}$, indicating that VC_1 will select either an L project or an S project, depending on the signal it observes. The points through μ_6 are the realizations of posterior beliefs given a series of L signals. Once within the region labeled $\{L\}$, in the bottom right of the triangle, any VC will choose an L investment regardless of its private signal. That is, this is the region in which L cascades form.

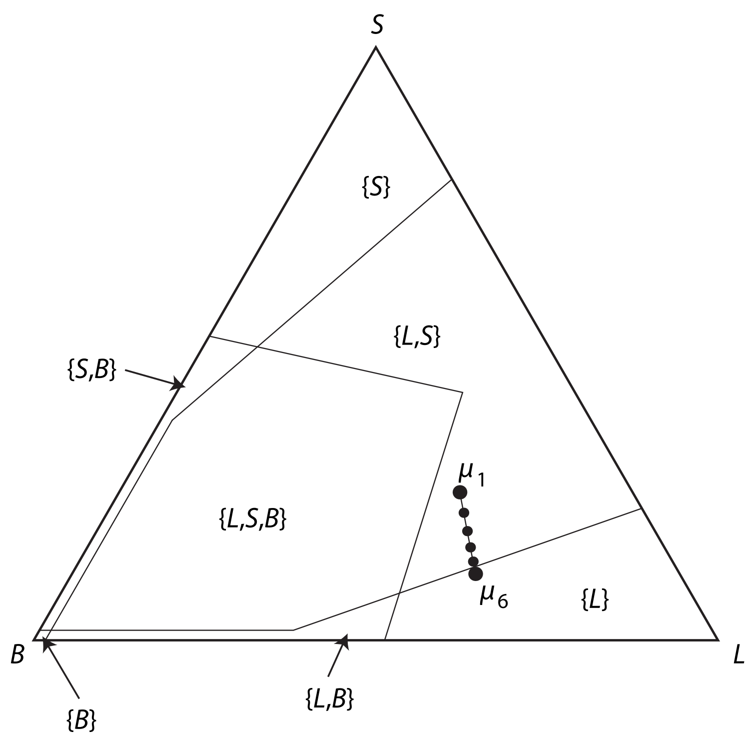

Figure 2: Secondary Cascade (from the Example in the Appendix)

Building on Figure 1, the point μ_7 indicates the VCs' prior beliefs in period 7, before the success or failure of the project from period 1 is realized. Note that $\mu_7 = \mu_6$, because the action of VC_6 is part of an L cascade and therefore is uninformative to the other VCs. The point $\hat{\mu}_7$ is the posterior belief in period 7 after VCs observe the failure of the L type project from period 1. The succeeding points through $\hat{\mu}_{10}$ represent the posterior beliefs through period 10, after the failure of the projects from periods 2–4 and the actions of VCs in periods 7–9 given a series of S signals. Since $\hat{\mu}_{10}$ falls into the region labeled $\{S\}$, an S cascade begins in period 10.

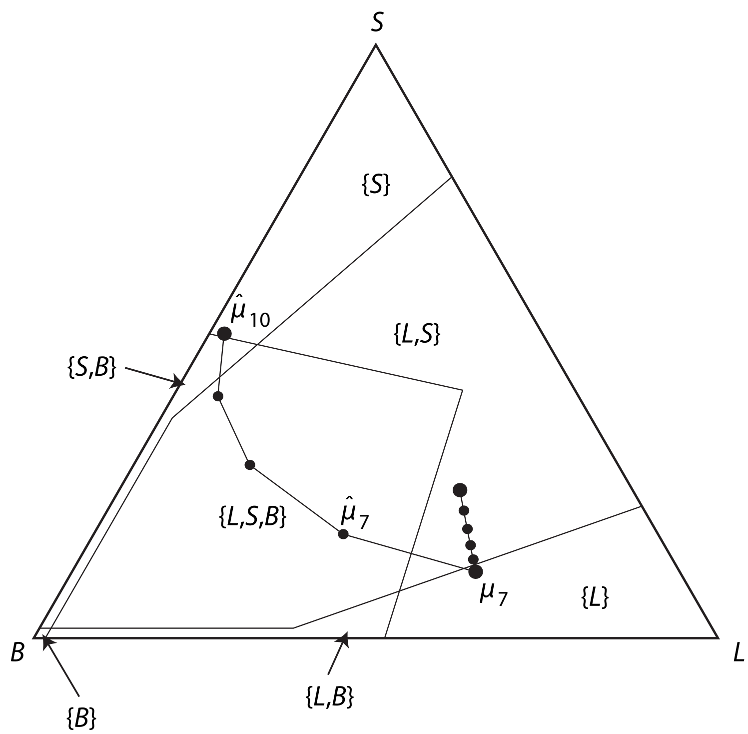

Figure 3: Cascades Under Alternative Parameters

These four figures display the same information as in Figure 2, but under alternative parameter values. In particular, π_L takes the values 11, 12, 13, and 14, rather than 10. All other parameters are the same as in the example in the Appendix. As π_L increases, the $\{L\}$ region grows, decreasing the number of L signals needed to initiate a cascade. The $\{B\}$ and $\{S, B\}$ regions shrink and eventually disappear.

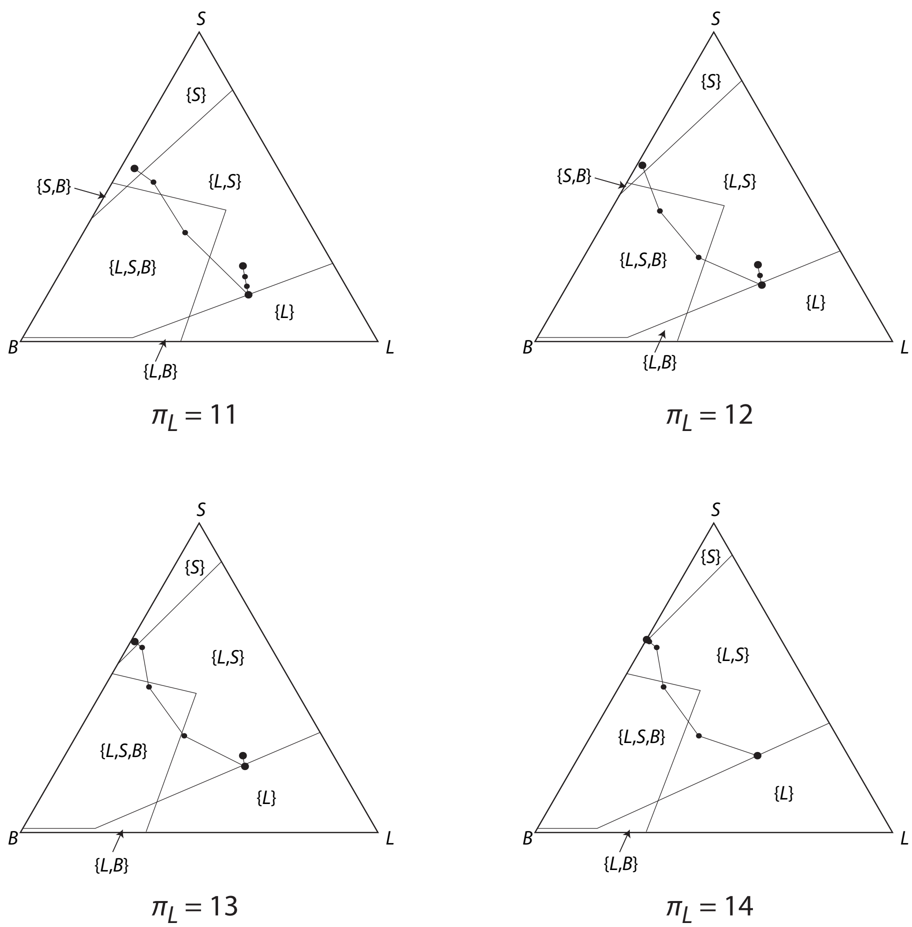

Figure 4: Timeline of Events and Investor Expectations (from the Example in the Appendix)

The events described in the example are displayed for periods 1–17. For each period t, σ_t is the signal observed by VC_t and a_t is the action chosen by VC_t. Signals that are ignored due to cascades are shown in light italics. In period 7, VCs start to observe the success (s) or failure (f) of projects started 6 periods earlier, and in period 8 investors start to observe the success or failure of projects started 7 periods earlier. As in Figures 1–2, cascades begin in periods 6 and 10. Investors' expected profits, net of the opportunity cost of not being able to invest directly in bonds, are shown at the bottom. In period 11, these expected profits become negative and so investors withhold their funds from venture capital. In period 14, their expected profits become positive again, so they return their funds to venture capital.

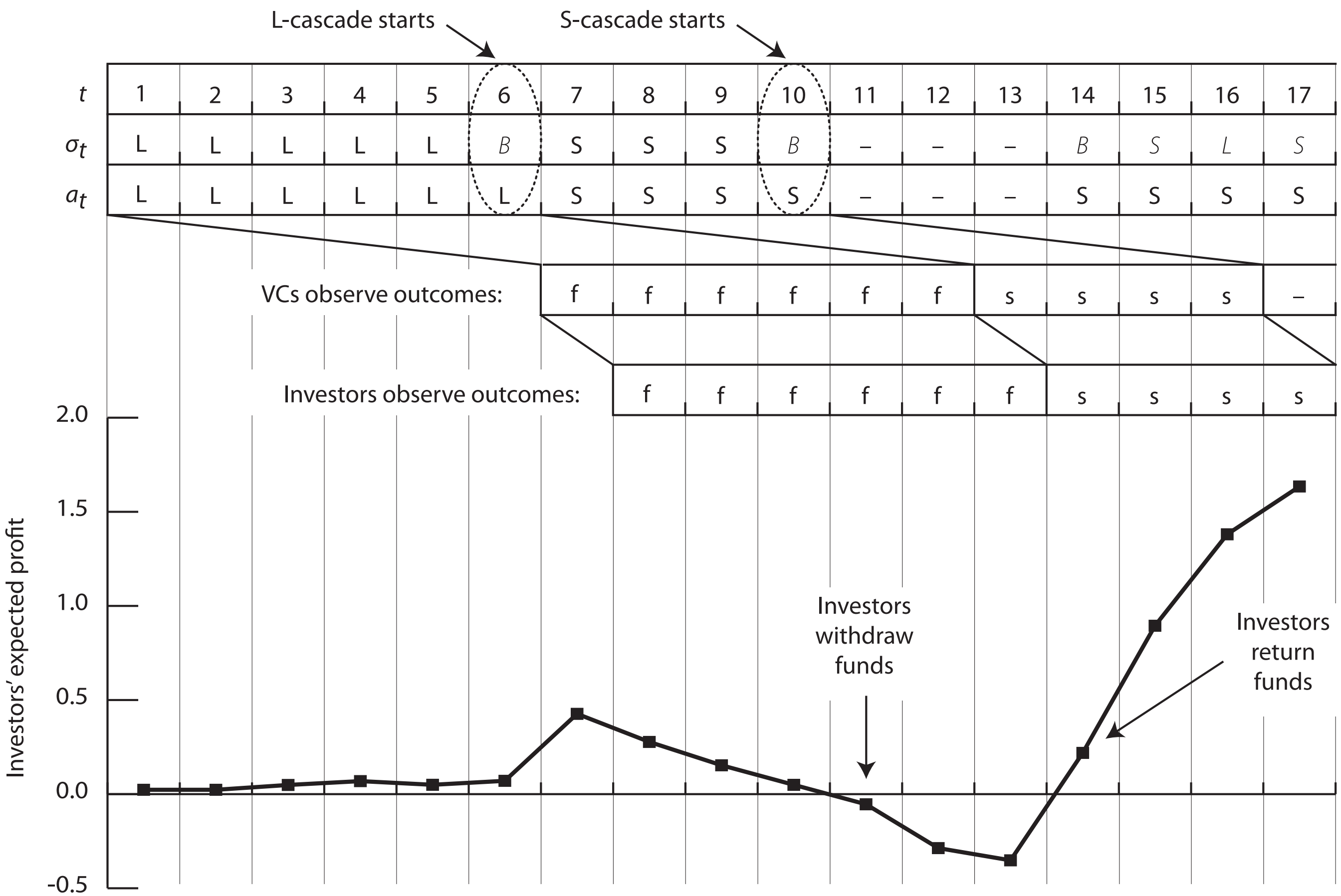

Figure 5: Relative Size of VC Financings by Category

The size of "PWC Moneytree" (independent venture related US based) deals of 13,014 target companies, 35360 deals, 1996–2004, as classified by Thompson Financial Venture Economics. All changes are reported relative to the first quarter of 1996. Deal sizes are grouped by target industry focus. *Non Hi-Tech* and *Biotech* reflect broad classifications. Venture Economics' third broad classification, *Information Technology* is broken into two strata, *Internet* firms and *non-internet IT* firms. Deals are pooled, regardless of round. The Source: Thompson Financial Venture Economics (VentureXpert)

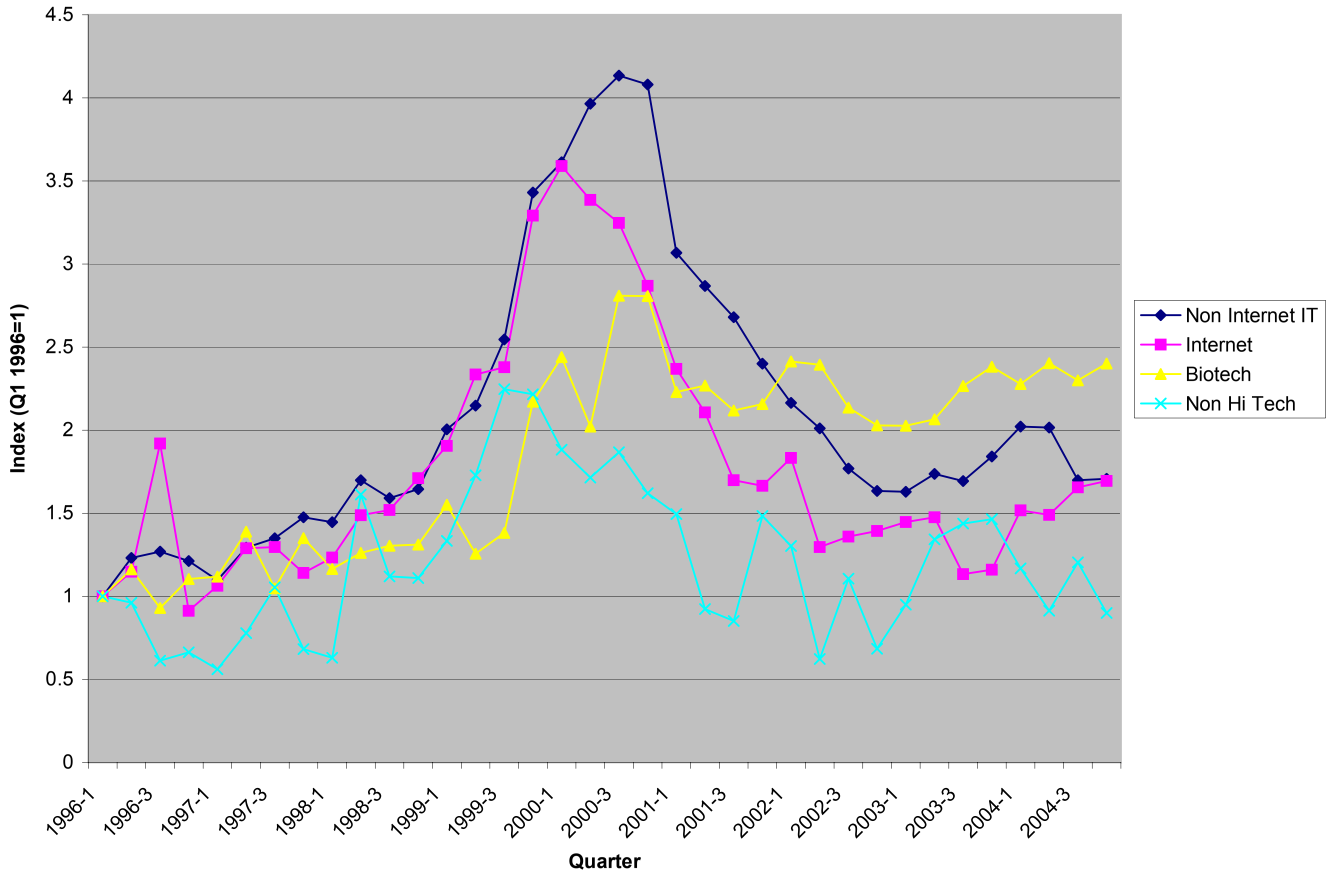

Figure 6: Relative Size of VC Financings of Internet Companies, First Rounds Only

First round "PWC Moneytree" (independent venture related US based) deals of 13,014 internet companies, 1996–2004, as classified by Thompson Financial Venture Economics. The size of "PWC Moneytree" (independent venture related US based) deals of internet companies, 1996–2004, as classified by Thompson Financial Venture Economics. All changes are reported relative to the first quarter of 1996. Deal sizes are grouped by target industry focus. *Non Hi-Tech* and *Biotech* reflect broad classifications. Venture Economics' third broad classification, *Information Technology* is broken into two strata, *Internet* firms and *non-internet IT* firms. Deals are pooled, regardless of round. The graph reports three month moving averages. Source: Thompson Financial Venture Economics (VentureXpert).

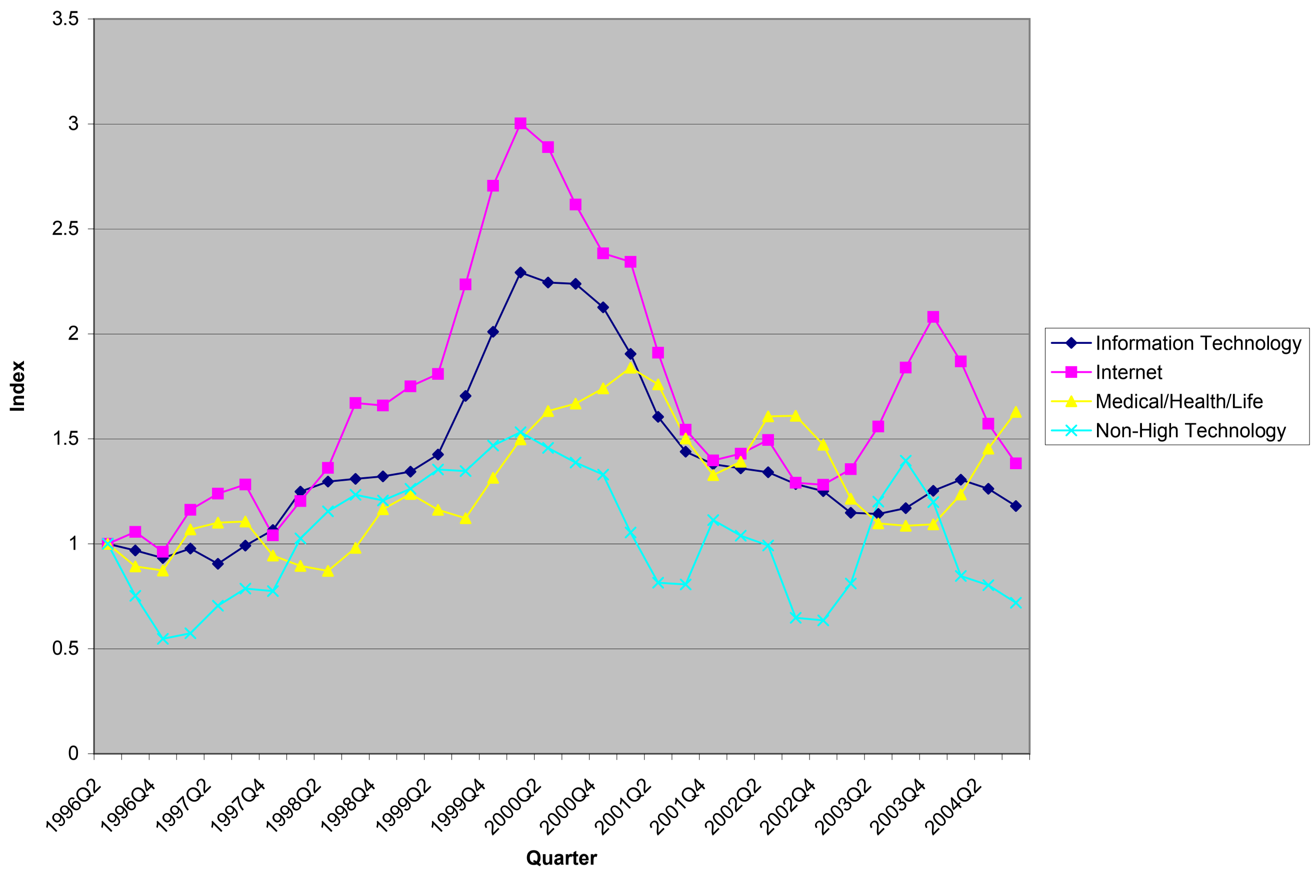

Figure 7: Internet IPOs 1996–2004

Depictecd are 272 IPOs of venture backed internet companies, 1996–2004, as classified by Thompson Financial Venture Economics. Source: Thompson Financial Venture Economics (VentureXpert)

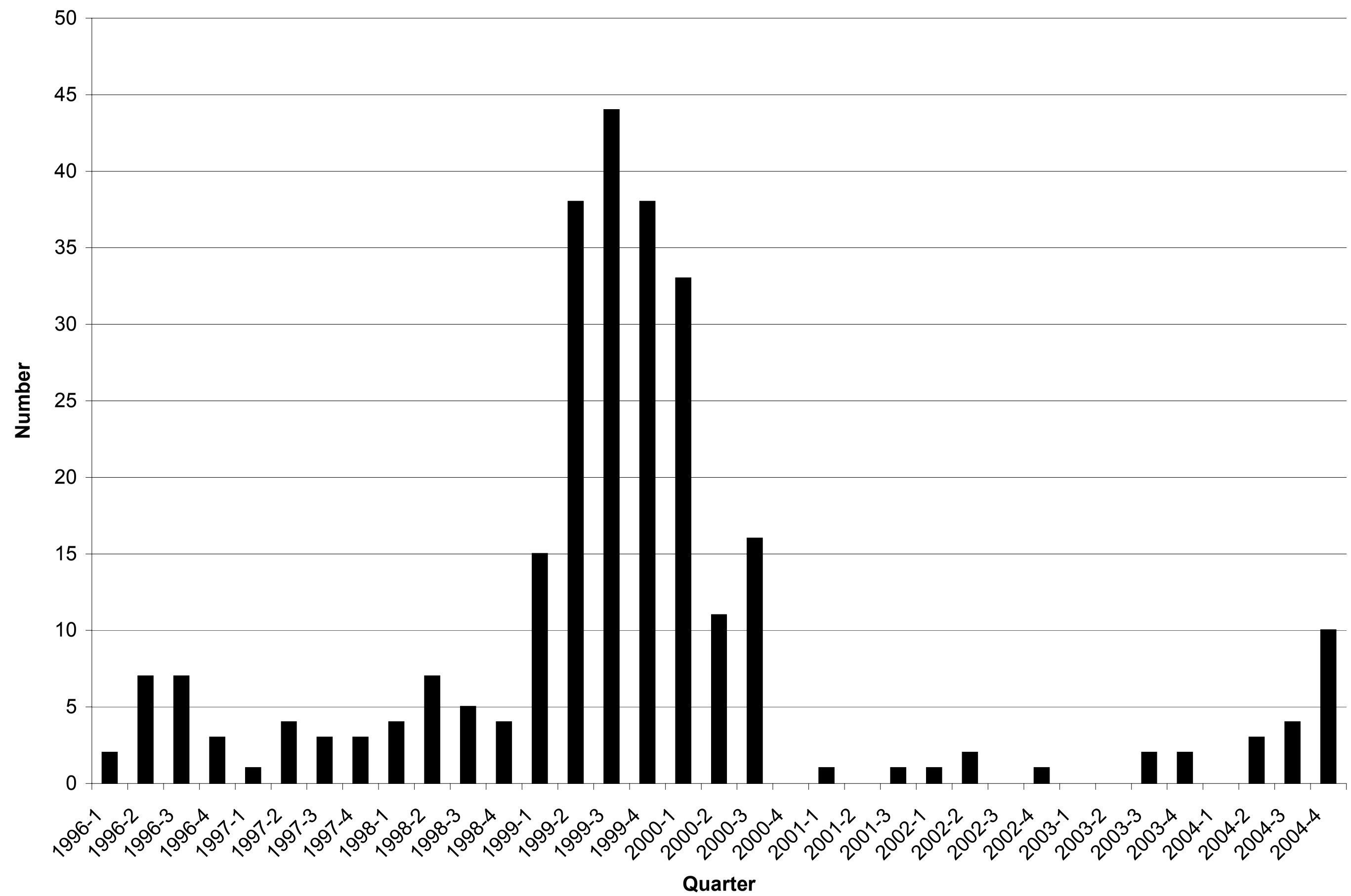

Figure 8: VC Fundraising of Internet-Focussed Funds 1996–2004

Commitments by limited partners to VC funds with declared internet specialization, 1996–2004. The chart describes the extent to VC fundraising for the purpose of financing internet firms. Source: Thompson Financial Venture Economics (VentureXpert)