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Working Paper 15-070

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Cost of Experimentation and the Evolution of Venture Capital

Michael Ewens, Ramana Nanda and Matthew Rhodes-Kropf*

Draft: March 2017

We study how technological shocks to the cost of starting new businesses have led the venture capital model to adapt in fundamental ways over the prior decade. We both document and provide a framework to understand the changes in the investment strategy of VCs in recent years - an increased prevalence of a "spray and pray" investment approach - where investors provide a little funding and limited governance to an increased number of startups that they are more likely to abandon, but where initial experiments significantly inform beliefs about the future potential of the venture. This adaptation and related entry by new financial intermediaries has led to a disproportionate rise in innovations where information on future prospects is revealed quickly and cheaply, and reduced the relative share of innovation in complex technologies where initial experiments cost more and reveal less.

JEL: G24, O31

Keywords: Innovation, Venture Capital, Investing, Abandonment Options

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Cost of Experimentation and the Evolution of Venture Capital

I. Introduction

Although technological change is increasingly seen as the primary driver of of productivity growth (Aghion and Howitt, 1992), adaptation by financial intermediaries may be equally important to realizing the benefits of these new technologies (King and Levine, 1993; Laeven, Levine, and Michalopoulos, 2015). For example, Chandler (1965) documents the adaptation by specialized investment banks as a response to the "vast sums of capital" required to finance the construction of railroads and govern industrial corporations needing arms-length capital from distant investors.[1] Similarly, Nicholas (2015) shows how the modern venture capital model arose in the mid-20th century in order to channel capital to the myriad new technologies emerging outside of the corporate R&D model.

We provide evidence that the venture capital investment model has evolved in fundamental ways over the last decade, particularly in the early stage financing of software and service oriented startup ventures. For these sectors, we document an increased prevalence of an investment strategy that has been colloquially referred to as "spray and pray," where early stage investors provide a little funding and limited governance to an increased number of startups, most of which they abandon after their initial investment. The "spray and pray" investment approach is a significant shift away from the traditional value-added 'governance' in the early stages of a venture's life and is particularly significant because venture capital investors are not just passive, but typically play a central role in monitoring and governing new ventures through a successful exit (Hellmann and Puri, 2000; Sorensen, 2007).

We argue that this change in the investment strategy of early stage investors has been driven by technological shocks that have substantially lowered the cost of starting new businesses, opening up a whole new range of investment opportunities that were not viable before, but also necessitating new ways of financing them. To understand the need for

[1] See also Alfred D. Chandler (1977); Baskin and Jr. (1997); Neal (1990), and Laeven et al. (2015).

this adaptation by early stage investors, it is helpful to recognize that a key feature of the venture capital context is a combination of extremely skewed ex post returns and an inability to tell the biggest successes ex ante (Hall and Woodward, 2010; Kerr, Nanda, and Rhodes-Kropf, 2014b). VCs therefore stage their investment across multiple rounds, and each round of investment can be seen as an experiment that generates information about the ultimate value of the startup. Critically, staging also allows VCs to abandon their investment if intermediate information is negative, so that each investment stage is akin to a real option (Gompers, 1995; Cornelli and Yosha, 2003; Bergemann and Hege, 2005; Fluck, Garrison, and Myers, 2007; Bergemann, Hege, and Peng, 2008; Tian, 2011). From a theoretical perspective, therefore, the falling cost of starting firms has a first order effect on the value of these real options. We provide a simple theoretical framework to highlight how the falling cost of starting firms can alter the way VCs select and govern their portfolio of investments due to the higher value of these abandonment options.

Our paper aims to provide a deeper understanding of how the changing cost of starting new ventures has impacted venture-capital backed entrepreneurship in the US. While anecdotal accounts of this phenomenon and the changes in the market for early stage finance have been documented in the press (e.g., (The Economist, 2014)) and the managerial implications popularized in frameworks such as the “lean startup model,” we are not aware of any systematic work examining how the changing cost of starting businesses impacts the early stage financing market. Our approach combines rich data on the investments and composition of venture capital portfolios with a theoretical framework that emphasizes a core mechanism driving our findings.

We begin by providing evidence of a changing investment approach by VCs following the advent of Amazon’s Web Services (AWS) in early 2006. The introduction of cloud computing services by Amazon is seen by many practitioners as a defining moment that dramatically lowered the initial cost of starting internet and web-based startups. Cloud computing allowed startups to ‘rent’ hardware space in small increments and scale up as demand grew, instead of making large fixed upfront investments in hardware when the probability of success for the startup was still extremely low. This allowed entrepreneurs and investors to learn about the viability of startups before making large fixed investments, and hence can be seen as lowering the costs of initial experiments. Importantly, this technological shock impacted only a subset of firms. The cloud services provided by AWS provided scalable bandwidth, storage and computing resources for companies with a strong online presence such as software-as-a-service, social networks, or retail e-commerce websites. This cross-sectional variation in the changing cost of starting firms allows us to systematically document our findings in a differences-in-differences framework.

We show that subsequent to the shock, startups founded in sectors benefiting most from the introduction of AWS raised significantly smaller amounts in their first round of VC financing. On average, initial funding size fell 20%, but quantile regressions demonstrate that this fall was across the board and even larger for many parts of the funding-size distribution. Importantly, we find that the fall is confined to initial startup costs. While startups in treated sectors raised less capital in their initial two years, total capital raised by firms in treated sectors that survived 3 or more years was unchanged. This is consistent with the notion that the primary effect that AWS had was on the *initial* fundraising by startups rather than on the cost of running the business at scale - effectively allowing startups to shift their large capital investments to later stages when uncertainty had been resolved.

We turn next to showing how this fall in the cost of starting businesses impacted the way in which VCs managed their portfolios. We show that in sectors impacted by the technological shock, VCs responded by providing a little funding and limited governance to an increased number of startups, which they were more likely to abandon after the initial round of funding. The number of initial investments made per year by VCs in treated sectors nearly doubled from the pre- to the post-period, without a commensurate increase in follow-on investments, and VCs making initial investments in treated sectors were less likely to take a board seat following the technological shock. In a reference to the large number of startups that receive an initial investment, the lower governance, and the smaller proportion of ventures that receive follow-on funding, this investment approach is colloquially referred to as one where investors "spray and pray".[2]

Our findings are consistent with anecdotal accounts of entry by several new financial intermediaries such as 'Micro-VCs' and 'Super Angels' who specialize in early stage investing using such an investment approach.[3] However, the inclusion of VC fixed effects in our regressions shows that this was not just a compositional shift in the types of investors before and after the shock - VCs who were active in the pre-period were also involved in deals where the initial funding size had fallen relative to their own deals in untreated sectors. Moreover, VCs who were active investors in the pre-period were more likely to invest through a spray and pray investment strategy in sectors that benefited from the technological shock. As noted above, the "spray and pray" investment approach is a significant shift away from value-added 'governance' in the early stages of ventures to more passive 'learning' about startup potential.

The falling cost of starting new businesses allowed a set of entrepreneurs who would not have been financed in the past to receive early stage financing. While these marginal ventures that just became viable had lower expected value, they seemed to be largely comprised of ventures with a lower probability of success, but a high return if successful (what we refer to as "long shot bets") rather than just 'worse' ventures with a lower gross return when successful. We find that in sectors impacted by the technological shock, VCs increased their investments in startups run by younger, less experienced founding teams. While these characteristics are consistent with anecdotal accounts of "long shot bets" such as Google, Facebook, Airbnb and Dropbox being founded by young, inexperienced founders,[4] it is of course also consistent more broadly with alternative mechanisms that would point to the marginal firm just being a worse investment. To help distinguish

[2]This "spray and pray" investment strategy is typified by a quote from Naval Ravikant, a prominent angel investor and founder of the platform AngelList, who noted that "making an [early stage] investment is like throwing darts in the dark." Source: Fatima Yasmine, February 22 2011, "Naval Ravikant: Twitter, Bubbles, New York and Start Fund [Interview Part 2]"

[3]Note that the term 'Super Angel' is somewhat of a misnomer, as these investors raise professionally managed funds from limited partners, operating effectively as early stage VCs rather than as angel investors.

[4]See Kerr et al. (2014b) for a description of how such ventures were not seen as sure bets and how reputable investors chose to pass on the chance to invest in them.

between these, we exploit the insight that "long shot bets" will see a greater increase in valuation in the event that they receive another round of funding. This is because long shot bets have a small chance of a huge payoff, so the relatively infrequent states of the world where the initial experiment generates positive information will lead investors to update their posterior beliefs about the startup's expected value much more - and hence lead to higher step-ups in value from the first to the second round of funding. Our empirical results document that relative to the pre-period, startups in treated sectors were more likely to fail, but conditional on another round of funding, had nearly 20% higher step-ups in value across rounds than equivalent startups in un-treated sectors. This finding is consistent with the notion that on balance, there was an increase in long shot bets being financed and is harder to reconcile with other potential channels through which VCs might respond to the falling cost of starting new ventures. We supplement our empirical results with a simple theoretical model that formalizes the intuition outlined above.

An interesting implication of our results is that the value added role of VCs may have fallen at precisely the point in the startup's lifecycle that value-add is needed the most. Moreover, younger and more-inexperienced founders, who have a technology that holds a lot of promise but are not experienced at running a firm, arguably need mentorship and governance even more than those run by more experienced entrepreneurs. Yet the fact that VCs need to "spray and pray" to make the investment profitable implies that these startups only get financed with limited governance. This finding helps to explain the rise of new financial intermediaries such as accelerators that provide *scalable*, lower cost forms of mentorship to inexperienced founding teams (and which have only emerged in the last decade), as these are a natural response to the gap in governance created by the evolution of VCs' investment behavior in early rounds to a more passive spray and pray approach (Hochberg, 2016). A second implication of our result points to a disproportionate increase in investments made in sectors with more discriminating early experiments, even if there is no change in the number of investments in sectors with a slower, or more costly, revelation of final project value. This change nevertheless alters the trajectory of aggregate innovation and is consistent with a common refrain in the popular press and among some prominent entrepreneurs that VCs are not devoting sufficient attention to backing 'fundamental' innovations in recent years.

Our work is related to the literature on early stage financing (Kerr, Lerner, and Schoar, 2014a; Hellmann and Thiele, 2015; Puri and Zarutskie, 2012) and the emergence in recent years of new financial intermediaries that select and shape startups at the earliest stages in their life (Cohen and Hochberg, 2014; Bernstein, Korteweg, and Laws, 2016; Gonzalez-Uribe and Leatherbee, 2015). Our paper provides a framework within which to view the emergence of these new financial intermediaries. Our results are also related to a small literature on financial innovations and the important role they play translating technological change into economic growth (Allen and Gale, 1994; Laeven et al., 2015)). Historical work on entrepreneurship in the United States has documented the central role of the financial innovations to commercialize new technologies as early as cotton and the railroads (Cain, 2010). More recently, Janeway (2012) notes how venture capital evolved to support the funding of biotechnology ventures. Our work builds on this line of research and documents the important feedback between technological change and financial intermediaries - technological shocks to investment opportunities require adaptation by investors. Indeed, without such adaptation, the benefits of new technologies may not be fully realized. Yet, this adaption also has consequences for the future trajectory of innovation by shaping the way in which financial intermediaries select and manage their investments.

The rest of the paper is structured as follows. In Section II, we describe how the introduction of Amazon Web Services impacted the cost of starting firms in certain industries, and provide a simple theoretical framework to guide the interpretation of our results. For interested readers, we note that a more comprehensive model on which the framework is based, available in an Internet Appendix. In Section III, we describe the data we use to more-systematically test these ideas and outline our identification strategy. Section IV outlines our results and Section V provides robustness tests. Section VI discusses how new intermediaries are responding to the gaps created by the evolution of traditional Venture

Capital and Section VII concludes.

II. Descriptive Evidence and Theoretical Framework

A. Cloud Computing

We first motivate our choice to use the introduction of cloud computing as the technological shock to identify adaptation by venture capital investors. A number of practitioners have pointed to the introduction of cloud computing as a defining moment when the initial cost of starting certain businesses fell.[5] Cloud computing services were first introduced by Amazon in early 2006. Our research suggests that the products included in Amazon's Web Services (AWS) were "developed first and foremost for Amazon's internal infrastructure" before opening these services up to developers outside Amazon in 2006, the timing of which was not anticipated by entrepreneurs or investors (Clark (2012); Vogels (2011)). Amazon's CTO Werner Vogels recalled that

> "At Amazon we had developed unique software and services based on more than a decade of infrastructure work for the evolution of the Amazon E-Commerce Platform. This was dedicated software and operation procedures that drove excellent performance, reliability, operational quality and security all at very large scale... The thinking then developed that offering Amazon's expertise in ultra-scalable system software as primitive infrastructure building blocks delivered through a services interface could trigger whole new world of innovation as developers no longer needed to focus on buying, building and maintaining infrastructure. AWS delivered the first storage service (Amazon S3) in the spring of 2006 and compute (Amazon EC2) in the fall of that year"(Vogels (2011)).

The ability to freely rent hardware in small increments that could scale with demand

[5] As described by Hardy (2014), "Cloud computing refers to an efficient method of managing lots of computer servers, data storage and networking. [This technological leap led to] immediate performance gains, since stand-alone servers typically used only a fraction of their capacity in case there was a surge in demand. By linking the machines together into a larger virtual system, the surge problem eased and a lot of computation was freed."

was not possible before 2006. Firms had to make large upfront investments in hardware to prepare for the small chance that they would be a success. The following quote by Mark Andreessen, a prominent venture capital investor and serial entrepreneur describes this process and the change:

> "In the '90s, if you wanted to build an Internet company, you needed to buy Sun servers, Cisco networking gear, Oracle databases, and EMC storage systems... and those companies would charge you a ton of money even just to get up and running. The new startups today, they don't buy any of that stuff... They're paying somewhere between 100x and 1000x [less] per unit of compute, per unit of storage, per unit of networking."

Andreessen also notes that the rise of services such as Amazons Elastic Compute Cloud (EC2) transformed many infrastructure costs from upfront capital expenditures to subscription services that could scale with a company as it grew, thereby reducing the fixed costs associated with starting new firms.[6]

Of course, 'renting' hardware is more expensive on a unit cost basis than buying the hardware outright. However, the ability to rent hardware allowed entrepreneurs to *initially* raise smaller amounts of capital to test technological viability and customer demand, only making large capital expenditures in hardware once their startup showed initial success and had achieved some scale. Thus, the primary effect of cloud computing was not to lower total costs, but rather to lower the cost of initial experiments when the probability of failure was high. A prominent example is that of Dropbox, which was founded in 2007, yet stored all the its files on Amazon's Cloud Computing servers until 2015, rather than on hardware that it owned and operated itself. Once it reached scale, however, management migrated to its own servers to improve unit economics. As Dropbox's vice president noted in an interview about why it stopped renting from Amazon, "Nobody is running a cloud business as a charity. There is some margin somewhere."(Metz, 2016).

[6]Source: Douglas Macmillan, "Andreessen: Bubble Believers "Don't Know What Theyre Talking About"," Wall Street Journal, January 3, 2014

B. A Simple Model of Multi-Stage Financing

We turn next to providing a simple model of multi-stage financing in order to illustrate how a fall in the cost of starting ventures might impact the investments made by VCs.[7] Consider an investor who stages their investment across two rounds, preserving the option to abandon their investment after the first stage if intermediate information is negative. Specifically, Let $E[p_2]$ denote the unconditional expectation about the second stage success. The investor updates their expectation about the second stage probability depending on the outcome of the first stage.[8] Let $p_S = E[p_2|S]$ denote the expectation of p_2 conditional on positive intermediate information (success in the first stage), while $p_F = E[p_2|F]$ denote the expectation of p_2 conditional on negative intermediate information (failure in the first stage).[9] Success in the second stage yields a total payoff of V, to be split between the entrepreneur and investor. Failure in the second stage yields a payoff of zero. The probability of 'success' (positive information) in the first stage is p_1.

The startup requires $\$X$ of capital in the first round and $\$Y$ in the second round of financing. The entrepreneur is assumed to have no capital while the investor has enough to fund the project for both periods. An investor who chooses not to invest at either stage can instead earn a safe return of r per period (investor outside option) which we normalize to zero for simplicity. The extensive form of the game played by the investor is shown in Figure 1.

In order to focus on the interesting cases, we assume that if the project 'fails' in the first period (i.e, intermediate information is negative), then it is NPV negative in the second period, i.e., $p_F * V < Y$. Further, if the project 'succeeds' in the first period (i.e., intermediate information is positive), then it is NPV positive in the second period, i.e.,

[7] While this simple model provides a theoretical framework within which to view our results, a more fleshed out *equilibrium* model of multi-stage financing in the Internet Appendix outlines how a shift in the cost of experimentation can not only impact marginal ventures but also have an impact on infra-marginal investments, thereby having a much larger impact on the way in which venture capital investors manage their portfolios.

[8] This might be the building of a prototype, initial traction with customers, or the FDA regulated Phase I trials on the path of a new drug, etc.

[9] One particular functional form that is sometimes used with this set up is to assume that the first and second stage have the same underlying probability of success, p. In this case p_1 can be thought of as the unconditional expectation of p, and $E[p_2|S]$ and $E[p_2|F]$ just follow Bayes' rule.

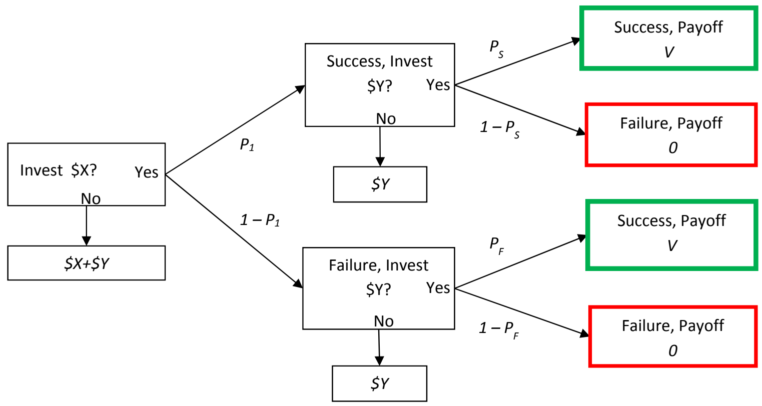

Figure 1. Extensive Form Representation of the Investor's Game Tree

$p_S * V > Y$. Without these assumptions the first stage 'experiment' is not relevant as, for example, $p_F * V > Y$ would imply that the investor will make the second round investment no matter what the result of the first stage investment is. We therefore assume that VCs will always abandon the investment if intermediate information is negative and always invest Y if intermediate information is positive. We further assume that VCs compete away rents, so that the NPV of their investment in each stage is always zero.

Note first that a VC will only be willing to invest in a startup if $p_1 * (p_S * V - Y) - X > 0$. Moreover, the minimum probability of first stage success that the VC will be willing to fund is:

$$p_{1\min} \equiv X/(p_S * V - Y) \tag{1}$$

It is intuitive that a fall in the cost of starting ventures, X, would lead to a larger number of investments from a VC's portfolio and – given partner time is a scarce resource – that this should lead to a fall in governance at the initial round of funding. However, note that the composition of ventures that get funded will also change. To see why, note that the denominator of equation (1) is the expected value of the startup at the second stage conditional on success in the first stage experiment, also referred to as the "pre-money valuation" of the venture at the second round of financing. Thus, the marginal venture which just becomes NPV positive when X falls is either one with a lower expected value conditional on initial success - we refer to these as "worse" startup ventures - or one with a lower p_1. Note that startups with a lower p_1 are ventures with greater option value, or "long shot bets", since they are more likely to fail, but conditional on positive intermediate information are equally likely to have a big success.

Of course, these are not mutually exclusive outcomes in that both "worse" ventures and "long shot bets" become viable investments when X falls. However, the model generates discriminating predictions that can help distinguish whether, empirically, on average, the increase in investments when X fell was driven by one type of venture or another. In particular, if the dominant driver is an increase in "long shot bets", we should see this manifested in three ways. First, we should find ex ante evidence of long shot bets, which we aim to capture empirically through the age and experience of founding teams when they are first funded. Secondly, if the increase in investments is dominated by ventures with a lower p_1 (as opposed to a lower $p_S * V - Y$), we should see an increase in failure rates following the initial round of funding (as opposed to initial failure rates remaining roughly constant). Finally, conditional on not failing after the first round, firms with a lower p_1 should see a higher step-up in value if they do get another round of funding and should have the same, or higher exit values when they eventually reach a liquidity event. The intuition behind a lower p_1 leading to a higher step is that if investors put a lower probability on the startup demonstrating intermediate success, seeing success after the first round of funding leads them to update their priors more, thereby leading to a higher change in valuation from the first round to the next. This intuition can be seen formally in the model by noting that the step-up in value – calculated as the pre-money valuation in round 2 divided by the post money valuation in round 1 – is inversely proportional to p_1.[10] Hence if the VCs' new investments are comprised mostly of long shot bets, we should

[10]To put this in terms of a numerical example, suppose there is a 20% chance of success in round 1 and a 40% chance of success in round 2. Initially it takes $4 million to reach round 2 and it takes a further $10 million in round 2 to reach an exit of $100 million. Assume that if the firm fails in either round 1 or round 2 it is worth zero. Working backwards, the post money valuation in round 2 will be $40 million (40% * $100 million) and the pre-money valuation in round 2 will be $30 million. Since the probability of success in round 1 is 20%, the post money valuation in round 1 is $6 million and the pre-money valuation in round 1 is $2 million and the VC would take 66.7% of the company in the first round of funding. Note also that the lowest probability of first round success that a VC would be willing to fund in round 1 would therefore be 4/30=13.33%. The step up from round 1 to

see higher step-ups in value for treated firms in the post period. On the other hand, if the dominant driver of the increased funding is worse investments, then p_1 will not change much and hence we should see little change in the step-ups of ventures being funded in the post-period.

III. Data and Estimation Strategy

We turn next to a systematic analysis of VC financings. Our analysis is based on the VentureSource database of venture capital financings, investors and entrepreneurial firms provided by Dow Jones.[11] However, the data are supplemented in several ways. First, additional valuation information for both financings and exits comes from Correlation Ventures and a merge of Thomson's VentureEconomics.[12] Second, additional information about the entrepreneurial firm's founding team comes from CapitalIQ, LinkedIn, Crunchbase, firm websites and Lexis Nexus.[13] Founders were identified with data from VentureSource and additional data collection detailed in Ewens and Fons-Rosen (2015).

We begin by including every first round of funding among VC-backed startups that occurred between 2002 and 2010 and was labeled as an early stage round of financing.[14] The focus is therefore on first, early stage financings of startups between 2002 and 2010. The final sample includes 8,961 entrepreneurial firms financed by 2,815 unique investors. The main sample has 16,944 observations at the investor-startup level of financing. Table I presents descriptive statistics for the key variables used in the analysis.

round 2 is $30/6 = 5$, which is inversely proportional to the probability of success from getting from one round to the next (1/20%). Suppose now that the first round of financing can be done with \$2 million instead of the original \$4 million. The minimum possible probability of first round success falls to $2/30 = 6.67\%$. That is, startups with a probability of initial success between 6.67% and 13.33% now become viable investments. But note that for a firm whose probability of initial success is 10% (not viable before but now viable), the step up from round 1 to round 2 (if the firm shows intermediate success) will be $1/10\% = 10$X.

[11] The coverage of financing rounds is extremely comprehensive in VentureSource and particularly so during our period of analysis, because scanned pdf versions of Form D filings were available on the SEC website for much of our sample period, making it much easier for data providers to collect comprehensive information.

[12] Correlation Ventures is an active venture capital fund that invests using a data-driven quantitative model.

[13] For each entrepreneurial firm founder, we matched using name and company to these separate data sources. The data sources provided past employment, person age, education background and gender. Lexis Nexus provides a service to collect individual birth years using name and state (of the company).

[14] We impose no further restrictions, either on the label of the round (e.g. only 'Seed Rounds' on the size of the round), as they are also impacted by the introduction of AWS and hence are endogenous. Nevertheless, we note that the results presented below are robust to dropping the small number of financing greater than \$25m or considering only seed rounds of financing.

A. Assigning Treated and Control Using Industry Variation

Importantly for our analysis, the advent of cloud computing in 2006 did not impact all industries equally. Its effects were confined to businesses with a strong online presence such as software-as-a-service, social networks, or retail e-commerce websites. Paul Graham, the founder of prominent accelerator, Y-Combinator, noted in 2008 that

> "[the reason] no one was doing quite what we do is that till recently it was a lot more expensive to start a startup. You'll notice we haven't funded any biotech startups. That's still expensive."[15]

We exploit this cross-sectional heterogeneity in the impact of cloud computing across industry sectors to identify the effect on venture capital investors. Specifically, we use narrow industry classifications assigned to entrepreneurial firms in the VentureSource database. VentureSource tracks venture capital activity in the United States and assigns industries to entrepreneurial firms by looking at the answer to the question "What is the essential product or service that the company provides?" We use the 26 distinct industry segments in VentureSource to create our definitions of "treated" and "control." Such segments include "Consumer Information Services," "Renewable and Non-Renewable Energy," and "Biopharmaceuticals." The goal is to assign each one of the twenty six categories to "treated" or "control" based on whether the typical firm in that industry classification benefited from the introduction of AWS. Firms that would benefit include those that provided online services, high-traffic websites, file storage or services, web hosting or online retail.

To facilitate assignment of industry to treated and control, we begin with an analysis of the companies in each industry segment. Table A.I in the Appendix provides a summary of the top ten words in the one paragraph company descriptions available in VentureSource across all firms in each industry segment from 2002 - 2010. Panel A presents the

[15]Source: http://paulgraham.com/ycombinator.html. Note also that in the past few years technological advances in other sectors – for example CRISPR/Cas genome editing techniques for biotechnology startups – have made it cheaper to start companies in biotechnology as well. This is why we limit our sample to a few years before and after 2006 to ensure a robust identification strategy.

list of keywords associated with the final eight treated industries from our classification. Popular words include "software," "web," "online" and "service." The introduction of the Amazon cloud effectively allowed firms such as these to outsource their backend online services in ways that were not possible prior to 2006. In Panel B, the eighteen control industries segments exhibit words that reference tangible goods such as "drug," "devices" and "system." The control classification includes firms who produce semiconductors or develop cancer drugs and thus have little to gain after the new cloud technology became available.

To formalize this intuition of firms that are most likely to benefit from AWS, we measure the fraction of firms whose description has at least one of the keywords "Online," "E-commerce," "Hosting" or "Web" in each industry segment, to provide an industry-segment-level exposure to the treatment. We deliberately choose not to define treatment at the firm-level as this is endogenous. Rather, we define treatment based on likelihood of benefit based on the description of activity among pre-period firms and show a strong correlation between this and activity among firms in the same industry-segment in the post-period. Table II provides the number of firms in each industry segment and the share of firms with at least one of the keywords above. As can be seen from column (4), the industry-segments categorized as "Treated" have a significantly higher share of the keywords compared to those in "Non-Treated" industries, where the prevalence is close to zero. In addition, it can be seen by comparing columns (2) and (4) that the incidence of these words increased in most of the Treated segments in the post period, while they remained equally non-existent in the the Non-Treated segments. Finally, by comparing columns (1) and (3), it can be seen that there is a disproportionate growth in number of firms entering treated segments in the post period compared to those in Non-Treated segments. This provides us with confidence that the words we are picking up are indeed good markers of industry segments that benefited from the introduction of AWS.

With this cross-sectional separation of entrepreneurial firms by exposure to the introduction of the Amazon cloud technology, the eight industry segments classified as treated are “Business Support Services,” “Consumer Information Services,” “Financial Institutions and Services,” “Media and Content,” “Medical Software and Information Services,” “Retailers,” “Software” and “Travel and Leisure.” Importantly, nearly all of these industry classification signal a service rather than production of good, and are likely to benefit from cloud computing due to their delivery of the service over the Web. The remaining eighteen industry segments classified as controls include “Aerospace and Defense”, “Biopharmaceuticals,” “Communications and Networking,” “Electronics and Computer Hardware,” “Healthcare Services,” “Machinery and Industrial Goods,” “Materials and Chemicals,” “Medical Device Equipment,” “Renewable and Non-Renewable Energy” and “Semiconductors.”[16] Importantly, the category “Communications and Networking” includes firms that produce hardware or sell services such “leased-line and dial up services”,“optical connectivity solutions”and “high-performance tunable lasers.” Similarly, Healthcare Services were less likely to be delivered over the web due to privacy concerns over this period.

B. Estimation Strategy

Our estimation strategy is a standard differences-in-differences regression. Given the timing of the technological shock, our analysis compares VCs' investments between 2006-2010 with the investments from 2002-2005. Also, since the technological shock disproportionately impacted early stage investments, our analysis focuses on the first, early stage round of funding among VC-backed startups, although as we show in the robustness section, we run placebo tests on later rounds of financing to highlight that indeed the shifts are driven by changes in the initial rounds of financing rather than changes across the board. Estimations are run at the VC firm-startup-year level and take the form:

$$Y_{jit} = \beta_1 Treated_i * Post_t + \beta_2 X_i + \gamma_t + \rho_j + \nu_{jit} \tag{2}$$

[16]The remaining categories are “Agriculture and Forestry,” “Construction and Civil Engineering,” “Food and Beverage,” “Household and office goods,” “Utilities,” “Vehicles and Parts,” and “Wholesale Trade and Shipping.”

where X_i are entrepreneurial firm characteristics at the time of the investment, including industry group fixed effects, geographic fixed effects and an indicator for whether the firm was in a treated industry segment, γ_t are year fixed effects corresponding to the year of the investment. In many specifications, we also include VC-firm fixed effects, ρ_j, so that the β_1 estimate represents the within-VC dynamics of the dependent variable Y_{jit}. The main coefficient of interest (β_1) is the interaction between *Treated* and *Post*.

Note that since the definition of treated and control firms is based on industry segments, which is more granular than broad industry group classifications, the inclusion of industry group fixed effects (such Biopharmaceuticals and Healthcare, Information Technology, etc.) in all our estimations effectively provides within-industry impacts of the treatment. This is particularly useful as venture capital firms often have a broad industry or sector focus for their investments. Note also that since (2) includes year fixed effects, the main effect of *Post* is not identified.

As with any differences-in-differences estimation strategy, our key identifying assumption is one of parallel trends – that is, that the "untreated" industry segments provide an appropriate counter-factual for what would have happened to the treated firms had they not benefited from the introduction of cloud computing. While the parallel trends assumption, by definition, cannot be proven, we aim to validate it in several ways. First, columns (1) and (3) of Table II document that the rate of investment in the Non-Treated sectors was quite comparable across the pre- and post-periods. Post-period investment in the Non-Treated sector rose by about 30% compared to the pre-period, rising from 350 firms per year in non-treated sectors receiving first financing from VCs to about 450 firms per year in the post period. On the other hand, investment into firms in treated sectors rose from about 375 firms per year to over 700 firms per year, showing that the changes we observe are driven by firms in the treated sectors, as opposed to, for example, a smaller fall in investments in the control group. In addition, we show in dynamic specifications that there is no evidence of pre-trends (and find in unreported figures that there was no differential trend by industry across any of the outcome variables in the pre-period), providing further support for the parallel trends assumption.

Our identification is also predicated on a second key assumption that no other systematic change in 2006 impacted precisely the set of firms we classify as treated, in a manner consistent with our findings but through some other channel. We address three such potential channels in detail in the robustness tests, documented in Section V of the paper, but briefly outline them here as well. First, we document that our results are not driven by any changes due to the financial crisis, which manifested itself relatively briefly in the venture capital industry towards the end of our sample and was mostly confined to 2009.

Second, we examine other potential technological changes to the VC opportunity set - for example the introduction of the iPhone and its related apps. Consistent with the view that very few of these apps were funded by VC investors, we find that excluding firms in any way related to the iPhone appstore does not impact our results at all. Finally, we address other potential channels - such as younger entrepreneurs needing more governance and hence needing more staging, or entry by new intermediaries driving up prices, leading to smaller investments - that are consistent with some of our results. We provide extensive evidence that these are unlikely to be the drivers of our findings as they cannot account for the full set of patterns we see.

IV. Results

A. Capital raised in first financing

We first document that the cost of starting businesses did fall following the introduction of Amazon Web Services (AWS) in 2006, as suggested by practitioners. Table III reports the estimation results from (2) where the dependent variable is log size of the investment in the first round round of funding for VC-backed firms in the period 2002-2010. Columns (1) - (3) include VC firms that were active at any point in the sample period. Columns (4) - (6) are run on the subset of VCs that had at least three investments in the pre-2006 time period (i.e. were active in the pre-period). For each set of firms, the first column includes only industry fixed effects, the second column adds year fixed effects and the third column further adds VC-firm fixed effects. As can be seen from Table III, there is a significant decrease in the capital invested by VCs in first financings for startups in treated industry segments. Relative to the non-treated industry firms, capital invested in treated startups is between 15 to 27% lower. This difference represents a $670 thousand to $1.3 million fall in the average capital invested in the first round of funding in the pre-period.[17] We can also see that the smaller investment amount was a function of both entry by new investors who wrote smaller checks as well as a change in behavior from incumbents. We will continue to see this in all of the regressions below. Thus the effects we find seem to stem both from entry as well as adaptation.

Table IV reports the results from quantile regressions estimated at the 25th, 50th and 75th percentiles, again for any VCs in the sample and for the subset that were most active. It documents that the initial funding size fell in these industry segments across all points in the funding size distribution, not just on average as seen in Table III. Figure 2 reports the results from a dynamic specification of Equation (2) where each point is an estimate of the interaction of year and treated dummies, relative to year 2006. The bands correspond to with 95% confidence intervals. The patterns in the figure demonstrate there is no pre-trend and that the timing of the falling cost of first financings is consistent with the introduction of AWS.

B. VC response: "Spray and Pray" investing

Changes in the Number of Investments

Having shown the falling cost of starting businesses in"treated" industry segments, we turn next to understanding its consequences for the investment strategies of VCs and the composition of their portfolios. First, we provide descriptive evidence of this by calculating

[17]Note that these magnitudes may seem small relative to what industry practitioners describe as the importance of the shock. This is likely in part due to the fact that we are assigning 'treated' status to industries rather than to firms to address concerns about endogeneity. Since not every firms in a treated industry is treated, this measurement error will tend to bias estimates towards zero.

the number of newly financed firms in treated and non-treated from 2002 to 2010. The ratio of these treated to non-treated numbers is reported in Figure 3, where a ratio of one implies that there were an equal amount of firms financed in the two categories. There is a marked increase in investments that persists in the post period suggesting a shift in the financing rates of treated industry startups.

We next test for this change in a regression context by studying the total number of first-time investments in entrepreneurial firms made by VCs in each year and industry. The count is scaled by the total investors in the round so large syndicated investments do not receive additional weight. A unit of observation is thus a VC firm, year and one of two industry groups – "treated" and "non-treated." For years with no investment activity by a given investor, the count is zero so that we have a balanced panel across investor-year-industry cells. The dependent variable of interest is the log of one plus this count. Table V reports the results for the sample of all VCs and those with pre-2006 investment activity.

Column (1) of Table V shows an increase in investments in treated industries after 2006 across all VCs. Column (2) show a similar magnitude when comparing changes in investment rates within a VC's portfolio over the sample period. When we condition on the sample of VCs who have pre-2006 investments (columns (3) and (4)) the magnitudes are slightly larger and still positive. The economic interpretation of the estimate in the final column suggests 1.5 additional investments every two years in a VC fund. As the typical VC fund invests in 10 - 15 investments, this increase represents a meaningful change in the composition of the portfolio. When combined with the results in Figure 3, these findings suggest that the VC industry as a whole substantially increased investments to treated sectors after 2005, although importantly, this increase did not come at the expense of investments in non-treated sectors.[18]

[18] In unreported analyses, we also examine fund raising by VC investors. We assign a fund as being focused on treated sectors if at least 75% of its investments in the first year are made in treated segments. Similarly, we define a fund as focused on non-treated sectors if less than 25% of its investments in the first year are made in treated segments. The remaining funds are those that are not specialized in either treated or non-treated segments. Studying both the number of funds raised and the total capital raised by funds over the sample period, we find no evidence of crowding out of non-treated segments.

Changes in governance

An increase in the number of investments implies that VCs are less likely to actively govern their portfolio companies, and instead emphasize a more passive learning role in the earliest stages of their investments. To measure governance, we identify whether any investor in the first financing took a board seat. Unfortunately, we cannot always date the timing of the board's creation and an individual investor's start date on the board. The sample of financings is thus smaller than that of the main analysis. If none of the investors in the first financing are ever listed as a board member, then we label the financing as having no board seat. If at least one investor can be identified as a first financing board member, then the financing is labeled as such. Table VI presents the results from linear probability models where the dependent variable takes the value of 1 if the VC is listed as a board member.

Columns (1) and (2) of Table VI present the main results where we first include all investors active in 2002-2010. The coefficient on "Treated X Post-2005" show a lower probability that a first financing has an investor with a board seat. The economic magnitude of these estimates suggest a 14% lower probability of an investor joining the board. The remaining columns of the table include only those financings with active investors with and without VC firm fixed effects. Column (3) shows that on average, the use of boards fell. Here the economic magnitude is a 21% lower probability an investor takes a board seat in the first financing. The last column indicates that this change is also present within-VC, including for the more active investors. Overall, the results indicate that the changes in governance styles are not just driven by a changing composition of investors with different governance styles, but also due to adaptation by existing investors to focus less on governance in the early stages of a firm's life.

C. *Characteristics of Portfolio Companies*

Characteristics of Founding Teams

We next examine empirically how the characteristics of VC-backed entrepreneurial firms changed after startup costs fell. Table VII presents the ex-ante characteristics of investments made by VCs to see if they shift in the post-2005 period. In particular, we consider two attributes of the portfolio companies - average age of the founders (to proxy more broadly for founder experience) and the specific entrepreneurial experience of the founding team. Columns (1) and (2) of Table VII examine whether the average age of the founding team in newly financed entrepreneurial firms changes after the introduction of AWS. A decrease in the average age of entrepreneurial firm founders would suggest that investors are investing in less experienced, riskier founding teams. The coefficient on the interaction term in both samples "Treated X Post" indicates a statistically significant drop in the relative age of founding teams in VC firm portfolios.

Next, columns (3) and (4) of Table VII study the relationship between the post-period treated investments and the entrepreneurial experience of founding teams. Here, the dependent variable is an indicator that takes the value of 1 if at least one of the founding team members has prior founding experience (i.e. serial entrepreneur). The coefficient estimates on the interaction terms are again negative and statistically significant, suggesting that VC investors in treated segments are more willing to back founders with less startup experience. While younger and less experienced founding teams could be consistent with either 'worse' teams or teams that are 'long shot bets', we note that one might have thought that investing in younger founders with less entrepreneurial experience would require *increased* governance. This makes the falling governance as evidenced by the fall in board activity early in the life of startups even more remarkable, and is a fact that we return to in the following section.

Outcomes of investments

Having shown that the ex-ante characteristics of entrepreneurial firms backed by VC changed after 2005, we next investigate whether these differences translate into outcomes and success rates. Recall that the theoretical framework highlighted how an increase in 'long shot bets' should be associated with an increase in failure rates following the first round of funding, but with higher step-ups in value for firms that did in fact receive follow-on financing. Table VIII shows first that initial investments in startups in "treated" industries in the post-period were less likely to receive a follow-on investment (i.e. reinvestment by VCs), and were more likely to fail. The results in columns (1) and (2) of Table VIII show the fall in follow-on rates in the treated group and also suggest that this effect was stronger for those that receive capital from active, incumbent investors. This result is particularly interesting in light of evidence that suggests that experienced VCs are potentially more likely to be failure tolerant (Tian and Wang (2014)). Consistent with anecdotal accounts, this suggests that even experienced VCs may be adapting their investment style towards more "spray and pray" in the early stages, particularly in industries where the cost of starting firms has fallen substantially and hence made abandonment options more valuable. The last two columns of Table VIII also show an increased likelihood of ultimate failure, again particularly driven by active incumbents changing their investment strategies in treated sectors.[19] The lower likelihood of receiving follow on funding is consistent with the notion that the marginal investments were long-shot bets, rather than just being worse firms.

We next also consider two measures of success to ascertain if those firms that did not fail differ in their outcomes. The first measure is the step-up in value across rounds, which captures the change in valuation from the post-money valuation in the initial round of financing to the pre-money valuation of the subsequent round of equity financing. The

[19] The large rise in initial number of financing events, combined with a smaller follow-on rate has been colloquially referred to as the "Series A crunch." However, investors seem to share the perspective that companies deserving of the next round of funding were receiving capital (http://www.geekwire.com/2014/deserving-companies-will-weather-series-crunch-vcs-say/)

second measure is the ratio of exit value to total capital invested (or "total economic return") for startups that ultimately had a successful exit. Columns (1) and (2) show that the increase in equity valuation – "step-up" – is 15 - 20% larger for the treated industry firms after 2005. The last two columns of Table IX show that this increased valuation change manifests itself in higher exit valuations to capital raised. Thus, both interim valuations increase and the economic returns are larger. Combined with the higher failure rates found in Table VIII, the evidence is in favor of a shift to higher option value rather than just lower quality investments after the treatment event of AWS. We further validate this hypothesis by looking at whether the step-ups in value and higher exit valuations are particularly high for younger teams and teams with no serial entrepreneurs (that is, those that we considered to be ex ante long shot bets). These results are documented in Table X and again provide support for the idea that it was the longer-shot bets that were driving the outcomes we see.

V. Robustness Checks

Thus far we have documented that post-2005, startups in industry segments that benefited from the introduction of cloud computing experienced a shift towards 'long shot bets' and that VCs changed the way in which they managed their portfolios towards a 'spray and pray' investment strategy. We posit that a core channel driving these results was the fall in initial cost founding new ventures following the introduction of cloud computing services by Amazon Web Services. Since this technological shock substantially lowered the initial costs needed to be incurred in order to learn about startups' viability, this was equivalent to a falling cost of experimentation and made the real options taken by VC investors in the first round of funding much more valuable. We show how an increase in 'long shot bets' due to the fall in cost of starting firms arises as a natural consequence of this experimentation channel. Viewed through this lens of experimentation, it can also be seen that a natural response by VCs to long shot bets is to shift to a 'spray and pray' investment strategy, putting a small amount of money into a larger number of firms, but reducing their governance of these firms until they have learned whether the startup finds intermediate success.

An important element of the narrative presented above is that the introduction of AWS primarily impacted the *initial* investment decisions of investors - thereby changing the cost of initial experiments. To validate this, we provide direct evidence to confirm that the shock had a first-order impact on the size of first rounds, but had little measurable effect on total fundraising by startups over the subsequent five years. Table XI presents regression estimates of log of total capital raised for each year after the firm's first financing event (up to 5 years). The sample includes financings of VCs who are active both pre- and post-shock and the models include VC firm fixed effects. The estimates make clear that the relatively smaller financings in treated industries are confined to the early years of firms. By three years after their initial capital raise, firms in treated and untreated industries exhibit no difference in capital raised. This is important because many alternative explanations that relate to different investment opportunities are about the level of capital required to run a business. Our evidence strongly suggests that AWS impacted initial startup cost rather than total cost, and hence restricts the set of potential explanations considerably. Relatedly, in unreported results we repeat the exercise studying first capital raised in Table III for second round financing size. We again find little evidence that the funding size changes outside of first-round financings.

While our results are consistent with an experimentation channel and the timing consistent with the introduction of AWS, our identification is also predicated on the assumption that no other systematic change in 2006 impacted precisely the set of firms we classify as treated, in a manner consistent with our findings but through some other channel. We therefore examine the predictions from a set of alternative channels and discuss the extent to which they can also explain our findings. We address three such potential channels in detail below.

First, we document that our results are not driven by any changes due to the financial crisis, which manifested itself relatively briefly in the venture capital industry towards the end of our sample and was mostly confined to 2009. For example, while there was a 25% fall in the number of deals from 2008 to 2009, deal volume actually *increased* 15% from 2009 to 2010. Moreover, since our specification includes year fixed effects, alternative explanations must include a reason why treated industries were impacted differentially in a manner that accounts for our results. If anything, one might expect the crisis to have had the *opposite* effect, by leading investors to cut back more on the most capital intensive industries such as biotechnology and energy - which were unaffected by AWS. Nevertheless we find that excluding new financings in the first full year of the financial crisis (2009) has no material impact on our results.

Second, we examine other technological shocks that may have changed investment opportunities for VCs. Two potential candidates are the growth of open-source software and the iPhone and its resulting mobile ecosystem. We perform several tests to show these are unlikely to be the drivers of the changes we see in our context. We use the Google feature that has tracked search term frequency on their search engine since 2004 to compare search traffic for Amazon EC2 to these alternative events. Figure A.I in the Appendix shows the rapid increase in the search for "EC2" after 2005, which is in line with our identification assumptions. The next two figures in the Appendix show search traffic for the App Store (Figure A.II) and open source software (Figure A.III). For the App Store, the interest level only rose in 2008, well after the shock we study and towards the end of our sample period. As a second test, we exclude firms from our sample that had a mention of mobile applications, iPhones, Android and other similar technologies.[20] This is to ensure that what we capture is not simply the impact of smart phones and mobile applications changing the opportunity set for VCs, impacting both the characteristics of portfolio companies and the investment strategy of VCs. The exclusion of this sub-sample has no material impact on our estimates, so we conclude that our results are not primarily driven by the introduction of the iPhone. Turning next to open source, there is a perception that improvement and

[20] We use the one paragraph description of the company's product and customers provided by VentureSource to identify such firms.

dissemination of certain programming languages such as such as Ruby on Rails, PHP and Python may have increased during our sample period, making it cheaper to start and staff software startups. Our search for the frequency of the terms "open source" as well as for Python, popular programming language used for many VC-backed firm's websites, suggests these were prevalent well before the introduction of AWS and were largely constant across our time period. Figure A.III shows this pattern for the "open source software" search. Ruby on Rails, which is another popular web programming framework introduced in July 2004, shows rapid increases in search frequency two years prior to the introduction of AWS and so is also unlikely to have driven these changes. More generally, however, we should note that the role that these programming languages may have played is in fact consistent with the thrust of our model. The cost of starting businesses has fallen in software and other industries as well, making abandonment options more valuable for VCs and leading to a shift towards a new investment strategy. Empirically, we need to look for a large shock that differentially impacted some industries but not others, and we believe that AWS is such a shock and is one that practitioners have argued drove a large change in the cost of starting new firms. This analysis does not discount the potential role of other factors such as open source that may have also impacted the initial cost of starting businesses and impacted VC investment through the experimentation channel.

Third, we address other potential channels - such as younger entrepreneurs needing more governance and hence needing more staging, or entry by new intermediaries driving up prices, leading to smaller investments - that explain some of our results. To do so, we first note that the experimentation channel predicts that a fall in the cost of learning should lead to *less* governance as investors 'spray and pray' and that conditional on initial success, firms should receive *higher* step-ups in value across rounds - since firms that in fact succeed when they had a small chance of success generate a significant amount of information that is incorporated in the next round's prices. These two predictions are difficult to generate together through other channels. For example, if initial competition bid up prices, we should expect to see *lower* steps for firms that ultimately succeeded, while in fact, we find the opposite is true. Alternatively, if the composition of entrepreneurs changed in ways that required more governance, we should see the increased staging (and smaller associated rounds of funding) come hand in hand with other forms of increased governance, such as VCs taking more board seats. Again, we find the opposite is true.

Aside from examining alternative channels, we also run robustness checks on our estimation equation, by modifying the difference-in-difference specification in two ways. To address the concern that our controls for industry and time are insufficient to capture aggregate trends that coincided with the introduction of AWS, we include a linear time trend in each of the models. Doing so does not impact the results. It is possible that AWS simply coincided with other events in the 2000s that were not proxied by the cloud or open source measures discussed. First note that the patterns observed in Figures 2 provide no evidence that the results are driven by years immediately around the treatment date. As an alternative test, we thus move the treatment year back and forward one year – 2005 and 2006 – to understand whether the results are a general phenomenon of the time period. We estimate the main models where 2005 is the treatment year and 2006 is the post-treatment year. Similarly, we estimate the models where 2006 is the pre-treatment year and 2007 is the post-treatment year. If there was no other shock in the years surrounding the introduction of AWS, then these estimates should be significantly attenuated relative to our core results. For capital raised and the other major variables, the results are insignificant with these specifications, further bolstering the effect being related to a shock experienced in 2006.

VI. Entry of New Intermediaries and Trajectory of Innovation

A. Entry

A natural implication of our results is that we should see an increase in financial intermediaries who specialize in 'spray and pray' investing. This is consistent with a rise in VC funds focusing on early stage investing, often referred to as 'Micro VCs' or 'Seed Funds'.

Our analysis also highlights the counter-intuitive notion that governance by VCs seems to have fallen for precisely the stages and the types of entrepreneurs who might need it the most. It suggests that a natural response to the fact that VCs have shifted their emphasis from governance to learning in the early stages of a venture would be entry of financial intermediaries that specialize in scalable forms of mentorship and governance in the early stages of a venture's life.

In fact, there has been massive entry by new intermediaries known as accelerators, defined as "fixed, cohort-based programs, including mentorship and educational components that culminate in a public pitch or demo day" (Hochberg (2016); Cohen and Hochberg (2014)). Cohen and Hochberg (2014) note that the first accelerator, Y-combinator was founded in 2005. Today, estimates of the number of accelerators range from 300 to over 2,000. Accelerators also help to screen deal flow for VCs through forums such as 'demo day', making the search process for long shot bets more efficient. In fact, Paul Graham, referring to Y-Combinator, notes that "We're not a replacement for venture capital funds. We occupy a new, adjacent niche... our m.o. is to create new deal flow, by encouraging hackers who would have gotten jobs to start their own startups instead. We compete more with employers than VCs."[21] Similarly, in studying a prominent accelerator, Gonzalez-Uribe and Leatherbee (2015) find the primary role it plays is that of mentorship, and find limited direct effect of financing it provides to new ventures.

B. *Trajectory of Innovation*

The effect that such a shift in the investment strategy has on innovation is ambiguous. On the one hand, it is likely to increase the chances of radical new business models - companies such as Airbnb, that was founded by young, inexperienced entrepreneurs and was by all accounts a "long shot bet" when it was founded.[22] On the other hand, the shift

[21]Source: http://paulgraham.com/ycombinator.html. Cohen, Fehder, Hochberg, and Murray (2016) provide further empirical support for this notion by documenting the extremely small amounts that accelerators invest on average, if they invest at all.

[22]For example, Kerr et al. (2014b) highlight how Fred Wilson of Union Square Ventures wrote about his "regret" at passing on Airbnb, a startup that lets people rent rooms or homes to prospective guests online. Started in 2008, Airbnb currently lists 500,000 properties in more than 34,000 cities across 192 countries, far larger than any hotel

in investment strategy is likely to make it much harder for more complex technologies where the costs of experimentation are higher or where there is a slower revelation of information about the startup's final value. For example, the very long time frames and costs associated with learning about the potential of renewable energy technologies or cancer therapies have led to relatively little financing of such ventures, despite intense societal interest (Fernandez, Stein, and Lo (2012); Nanda, Younge, and Fleming (2015)).

VII. Conclusion

We study rich, novel data on the characteristics of VC-backed firms to show how technological shocks to the initial cost of starting new firms have had a fundamental impact on the way in which investors manage their portfolios and the types of companies they choose to finance. The falling cost of experimentation makes abandonment options for investors much more valuable and this directly impacts the types of firms that investors are willing to finance, as well as the investment strategy they choose to use. In particular, we show how technological shocks to the cost of experimentation can play a central role in shaping both the rate and trajectory of startup innovation, by allowing more long shot bets to receive initial funding and thereby also reducing the chance of 'false negatives' in the economy. Nevertheless, this comes hand in hand with an investment strategy where several startups receive a small initial investment, but who do not get follow-on funding when intermediate information is negative. We show how this adaptation of investors towards a "spray and pray" investment strategy will tend increase VC investment in startups where information is revealed quickly and cheaply and hence may adversely impact the extent to which more complex technologies, where information is revealed more slowly, are funded. In doing so we document the important feedback between technological change and financial intermediaries - technological shocks to investment opportunities require adaptation by investors, but this adaption has consequences for the future trajectory of innovation.

chainthereby making it the largest lodging company and brand in the world (Levere (2013)). Fred Wilson writes of Union Square Venture's decision to pass on the deal in 2009 that "we couldn't wrap our heads around air mattresses on the living room floors as the next hotel room.... Others saw the amazing team that we saw, funded them, and the rest is history." (Source: http://avc.com/2011/03/airbnb/)

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VIII. Figures and Tables

Figure 2. Difference-in-difference estimates for first capital raised: treated and non-treated

Notes: The figure plots the coefficients for the interaction terms of each financing year and the treated industry dummy for an OLS regression where the dependent variable, K_{it}, is the log of the first VC capital raised and the unit of observation is an entrepreneurial firm's first financing event. The 2006 interaction term is the excluded category, reported as zero in the figure. The vertical red lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

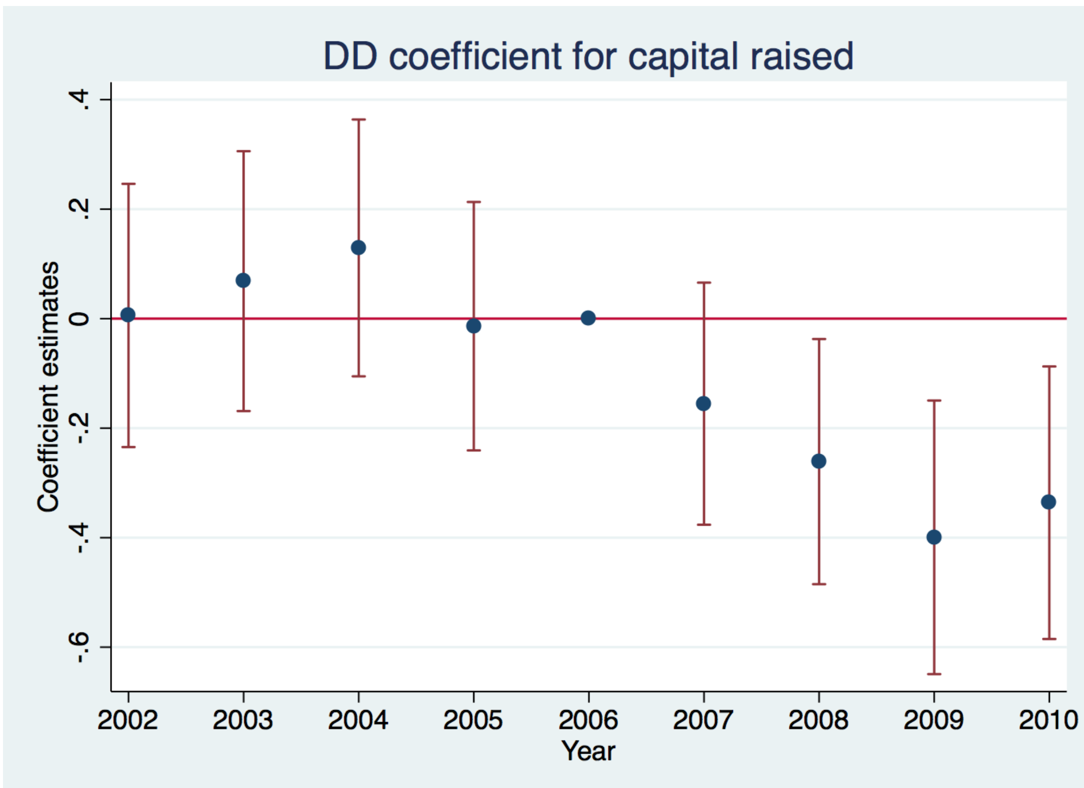


Figure 3. New VC-backed firms in treated industries

Notes: This figure reports the ratio of treated companies to untreated companies receiving a first, early stage financing as reported by VentureSource. A treated company is in one of the following industries (from VentureSource): "Business Support Services," "Consumer Information Services," "Financial Institutions and Services," "Media and Content," "Medical Software and Information Services," "Retailers," "Software" and "Travel and Leisure." A ratio of one implies that there were an equal amount of new entrepreneurial firms financed in that year in treated and untreated industries. The vertical red line represents the approximate date of the introduction of Amazon Web Services, our treatment event.

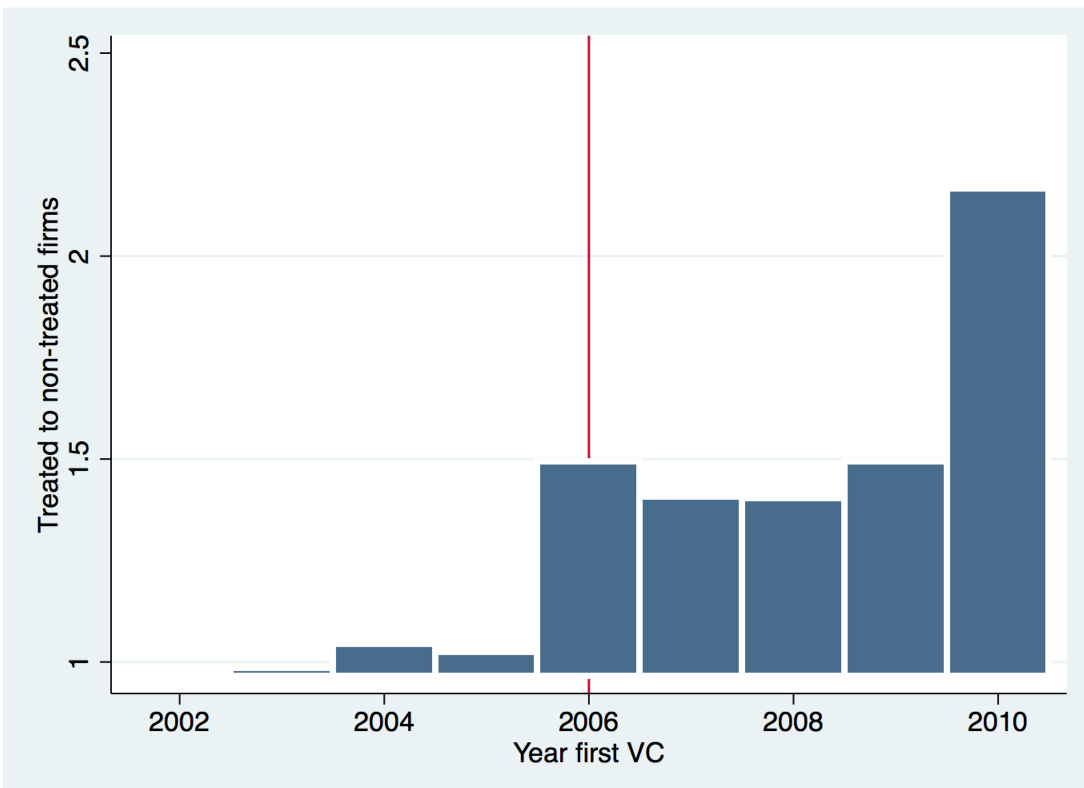


Table I—Descriptive statistics

Notes: This table reports descriptive statistics on US-based startups that received Seed or Series A financing from an investor in the Venture Source database between 2002 and 2010. The characteristics of firms and entrepreneurs are reported as of the date of first funding. "First capital (m)" is the first capital raised in the firm's first VC financing. "Firm age (yrs)" is the age of the startup at the time of first financing. "Team age (yrs)" is the average age of the founding team at the time of first financing. "Serial founders" is the fraction of firms that have at least one repeat founder on the founding team. "% failed" is the fraction of firms that went out of business by the end of 2015. "% follow on" is the fraction of firms that had a follow on investment by the end of 2015. "Step up in value" reports the ratio of pre-money in the subsequent round to the post-money of the current round (if both are available). "Exit value to capital" is the reported exit valuation divided by the total capital raised by the entrepreneurial firm. "% first board" is the fraction of firms that had at least one investor who took a board seat in the first financing round. The "# firms" reports the total number of firms for which we can calculate the variable.

	2002-2010			
	Firms	Mean	Median	Std. Dev.
First capital (m)	7,878	4.39	2.30	6.32
Firm age (yrs.)	8,804	2.15	1.23	2.77
Team age (yrs.)	5,717	40.28	40.00	9.04
Serial founder	7,903	0.26	0.00	0.44
% failed	8,961	0.51	1.00	0.50
% follow on	8,961	0.57	1.00	0.50
Step up in value	1,066	2.24	1.63	5.00
Exit value to capital	1,538	10.22	3.52	54.58
% first board	5,914	0.14	0.00	0.34

Table II—Treated vs. Non-Treated Industry Segments

Notes: This table documents the categorization of industry segments to "Treated" or "Non-Treated." It uses the description of each firm to characterize the degree to which the introduction of AWS was likely to be beneficial to the firm in its early stages. In particular, it measures the fraction of firms whose description has at least one of the keywords "Online," "E-commerce," "Hosting" or "Web" in each industry segment, to provide an industry-segment-level exposure to the treatment. We deliberately choose not to define treatment at the firm-level as this is endogenous. Rather, we define treatment based on likelihood of benefit based on the description of activity among pre-period firms, show a strong correlation between this and activity among firms in the same industry-segment in the post-period. The column "Number firms" presents the count of firms with the industry classification, while the column "word share" provides the ratio described above. "2002-2010" refers to firms in the full sample period, while "2002-2005" refers to the measure based on pre-period firms only. We lose 47 firms because they lack a business description or industry classification.

Industry Segment	Panel A: Treated industries			
	# firms	Word share	# firms	Word share
	2002-2005		2002-2010	
Business Support Services	277	24%	1195	27%
Consumer Information Services	137	53%	1061	55%
Financial Institutions and Services	79	11%	271	18%
Media and Content	53	22%	252	35%
Medical Software and Information Services	76	11%	225	14%
Retailers	45	13%	111	33%
Software	840	7%	1941	13%
Travel and Leisure	32	31%	89	27%
Industry Segment	**Panel B: Non-treated industries**			
	# firms	Word share	# firms	Word share
	2002-2005		2002-2010	
Aerospace and Defense	12	0%	31	0%
Agriculture and Forestry	5	0%	26	0%
Biopharmaceuticals	347	0%	910	0%
Communications and Networking	187	2%	359	2%
Construction and Civil Engineering	20	0%	72	0%
Electronics and Computer Hardware	141	3%	361	2%
Food and Beverage	16	0%	75	0%
Healthcare Services	62	2%	162	4%
Household and Office Goods	5	0%	47	2%
Machinery and Industrial Goods	20	0%	108	0%
Materials and Chemicals	49	0%	135	0%
Medical Devices and Equipment	292	0%	806	0%
Non-Renewable Energy	14	0%	41	0%
Personal Goods	19	0%	62	3%
Renewable Energy	36	0%	252	0%
Semiconductors	176	1%	269	1%
Utilities	0	0%	14	0%
Vehicles and Parts	5	0%	34	0%
Wholesale Trade and Shipping	1	0%	5	0%

Table III—Initial funding size

Notes: This table reports results from OLS regressions where the dependent variable is the log of initial investment for the startup in which a given VC invested. A unit of observation is an entrepreneurial firm financing associated with an investor. VCs who are active in the pre-period are defined as those investors with at least three investments in the pre-2006 period. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Syndicate size" is the log of the number of investors in the financing and the three "Startup based in" variables are dummies for entrepreneurial firm headquarters state. "Year FE" indicate dummies for financing year, "Industry FE" are dummies for the five major industries. "VC firm FE" are VC firm fixed effects. Standard errors are clustered by VC-firm. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All VCs			VCs active in pre-period		
	(1)	(2)	(3)	(4)	(5)	(6))
Treated X Post-2005	-0.294***	-0.269***	-0.152***	-0.319***	-0.308***	-0.148***
	(0.0663)	(0.0673)	(0.0375)	(0.117)	(0.117)	(0.0503)
Treated	-0.0293	-0.0338	-0.124***	-0.0732	-0.0739	-0.158***
	(0.0504)	(0.0504)	(0.0322)	(0.0675)	(0.0661)	(0.0393)
Syndicate size	0.323***	0.325***	0.233***	0.356***	0.356***	0.238***
	(0.0200)	(0.0197)	(0.00886)	(0.0371)	(0.0368)	(0.0118)
Startup based in CA	0.438***	0.424***	0.129***	0.484***	0.475***	0.0956**
	(0.0773)	(0.0766)	(0.0300)	(0.129)	(0.129)	(0.0380)
Startup based in MA	0.465***	0.453***	0.175***	0.539***	0.532***	0.169***
	(0.0797)	(0.0792)	(0.0388)	(0.141)	(0.141)	(0.0479)
Startup based in NY	0.276***	0.290***	0.0934	0.205	0.221	-0.0718
	(0.0743)	(0.0740)	(0.0602)	(0.146)	(0.145)	(0.0770)
Post-2005	0.0741*			0.179***		
	(0.0435)			(0.0665)		
Observations	15526	15526	15526	7708	7708	7708
Number startups	7878	7878	7878	5062	5062	5062
Number VCs	2647	2647	2647	506	506	506
R^2	0.117	0.130	0.108	0.138	0.143	0.119
Industry FE?	Y	Y	Y	Y	Y	Y
Year FE?	N	Y	Y	N	Y	Y
VC firm FE?	N	N	Y	N	N	Y

Table IV—Initial funding size: quantile estimates

Notes: This table reports results from quantile regressions where the dependent variable is the log of initial investment for the startup in which a given VC invested. A unit of observation is an entrepreneurial firm financing associated with an investor. VCs who are active in the pre-period are defined as those investors with at least three investments prior to 2006. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year, "Industry FE" are dummies for the five major industries and "VC firm FE" are VC firm fixed effects. Bootstrapped standard errors (500 repetitions) are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All VCs			VCs active in pre-period		
	25th pctile	Median	75th pctile	25th pctile	Median	75th pctile
	(1)	(2)	(3)	(4)	(5)	(6))
Treated X Post-2005	-0.216***	-0.301***	-0.230***	-0.223**	-0.170***	-0.149***
	(0.0609)	(0.0497)	(0.0413)	(0.110)	(0.0629)	(0.0531)
Treated	-0.0465	-0.205***	-0.240***	-0.167**	-0.247***	-0.262***
	(0.0601)	(0.0473)	(0.0291)	(0.0825)	(0.0471)	(0.0374)
Syndicate size	0.300***	0.248***	0.247***	0.343***	0.251***	0.242***
	(0.00902)	(0.00756)	(0.00853)	(0.0160)	(0.0130)	(0.00824)
Startup based in CA	0.437***	0.388***	0.244***	0.526***	0.429***	0.220***
	(0.0323)	(0.0254)	(0.0201)	(0.0607)	(0.0351)	(0.0277)
Startup based in MA	0.570***	0.471***	0.277***	0.718***	0.472***	0.245***
	(0.0462)	(0.0444)	(0.0336)	(0.0716)	(0.0435)	(0.0375)
Startup based in NY	0.348***	0.197***	0.200***	0.127	0.103	0.0752
	(0.0551)	(0.0633)	(0.0672)	(0.118)	(0.101)	(0.0880)
Observations	15584	15584	15584	7738	7738	7738
Number startups	7897	7897	7897	5078	5078	5078
Number VCs	2657	2657	2657	506	506	506
R^2 / psuedo-R^2	0.176	0.176	0.173	0.185	0.184	0.177
Industry FE?	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y
VC firm FE?	N	N	N	N	N	N

Table V—Total investments by investors

Notes: This table reports results from results of OLS and VC firm fixed effects regression total investments made by investors. Total investments are scaled by the number of investors in each first-round investment to ensure that entrepreneurial firms with more investors do not receive additional weight. A unit of observation is a quarter and industry, where industry is treated or non-treated as defined in Table II. For columns (1) and (2), all VCs are included in the analysis in OLS and FE specification respectively. Columns (3) and (4) have the same specifications for the sample of VCs who have investments in the pre-period (i.e. "Active" VCs). Industry fixed effects control for the five industry groups: Biotechnology and healthcare, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year and "VC firm FE" are VC firm fixed effects. Standard errors clustered by quarter are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Log total investments in quarter-industry			
	All VCs	All VCs	"Active" VCs	"Active" VCs
	(1)	(2)	(3)	(4)
Treated X Post-2005	0.0277***	0.0412***	0.0453***	0.0506***
	(0.00772)	(0.00850)	(0.0117)	(0.0113)
Treated	0.0136**	0.0152**	0.0140**	0.0158**
	(0.00585)	(0.00688)	(0.00642)	(0.00754)
Observations	30340	30340	17066	17066
Number VCs	2813	2813	506	506
R^2	0.0254	0.0215	0.0296	0.0230
Industry FE?	N	N	N	N
Year FE?	Y	Y	Y	Y
VC firm FE?	N	Y	N	Y

Table VI—Portfolio management by VCs: early stage governance

Notes: This table reports results from results of OLS and VC firm fixed effects regression for the indicator of a board seat at the time of the firm's first financing. A unit of observation is an entrepreneurial firm financing associated with an investor. VCs who are active (columns (3) and (4)) in the pre-period are defined as those investors with at least three investments in the pre-period. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year and "VC firm FE" are VC firm fixed effects. Standard errors are clustered by VC-firm are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All VCs (1)	All VCs (2)	"Active" VCs (3)	"Active" VCs (4)
Treated X Post-2005	-0.0266	-0.0301	-0.0616**	-0.0534**
	(0.0171)	(0.0188)	(0.0251)	(0.0268)
Treated	0.0159	0.000412	0.0584**	0.0252
	(0.0181)	(0.0177)	(0.0232)	(0.0251)
Syndicate size	0.0856***	0.0642***	0.105***	0.0750***
	(0.00377)	(0.00394)	(0.00554)	(0.00541)
Startup based in CA	0.0426***	0.00598	0.0587***	0.0110
	(0.0120)	(0.00953)	(0.0189)	(0.0164)
Startup based in MA	0.0617***	0.0425**	0.0682***	0.0554**
	(0.0167)	(0.0199)	(0.0232)	(0.0273)
Startup based in NY	0.0511***	0.0266	0.0737**	0.0271
	(0.0166)	(0.0170)	(0.0329)	(0.0316)
Observations	10250	10250	4760	4760
Number startups	5913	5913	3461	3461
Number VCs	2158	2158	500	500
R^2	0.105	0.0693	0.127	0.0752
Industry FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
VC firm FE?	N	Y	N	Y

Table VII—Ex ante characteristics of portfolio companies

Notes: This table reports results from results of VC firm fixed effects regression for founder characteristics at the time of first financing. A unit of observation is an entrepreneurial firm financing associated with an investor. The dependent variable in columns (1) and (2) is the log of the average entrepreneurial team age at the time of financing. The dependent variable in columns (3) and (4) is an indicator that equals one if at least one of the founders is a serial entrepreneur at the time of the financing event. VCs who are active in the pre-period (columns (2) and (4)) are defined as those investors with at least three investments in the pre-period. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year and "VC firm FE" are VC firm fixed effects. Standard errors clustered by VC-firm reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Log founding team age		Serial entrepreneur?	
	All VCs	"Active" VCs	All VCs	"Active" VCs
	(1)	(2)	(3)	(4)
Treated X Post-2005	-0.0519***	-0.0441***	-0.0431**	-0.0505**
	(0.0103)	(0.0101)	(0.0177)	(0.0233)
Treated	-0.0348***	-0.0373***	0.0887***	0.0916***
	(0.00689)	(0.00869)	(0.0143)	(0.0190)
Startup based in CA	-0.0485***	-0.0487***	0.0730***	0.0617***
	(0.00660)	(0.00730)	(0.0133)	(0.0156)
Startup based in MA	-0.00954	-0.0142	0.0538***	0.0651**
	(0.00652)	(0.00924)	(0.0190)	(0.0291)
Startup based in NY	-0.0654***	-0.0806***	0.0136	-0.0285
	(0.00957)	(0.0166)	(0.0172)	(0.0263)
Observations	11201	5623	15266	7589
Number startups	5717	3727	7902	5042
Number VCs	2171	500	2594	505
R^2	0.103	0.0965	0.0141	0.0143
Industry FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
VC firm FE?	Y	Y	Y	Y

Table VIII—Portfolio management by VCs: likelihood of startup failure

Notes: This table reports results from linear probability models for two outcome variables. A unit of observation is an entrepreneurial firm financing associated with an investor. Columns (1) and (2) use the indicator for the entrepreneurial firm having a subsequent exit or follow-on refinancing. Columns (3) and (4) use the dummy variable that is one if the firm failed by the end of the sample. VCs who are active (columns (2) and (4)) in the pre-period are defined as those investors with at least three investments in the pre-period. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. Industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year, and "VC firm FE" are VC firm fixed effects. Standard errors are clustered by VC-firm are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Follow on?		Failed?	
	All VCs	"Active" VCs	All VCs	"Active" VCs
	(1)	(2)	(3)	(4)
Treated X Post-2005	-0.0193	-0.0518**	0.0117	0.0535**
	(0.0169)	(0.0231)	(0.0200)	(0.0238)
Treated	0.0486***	0.0516***	-0.125***	-0.137***
	(0.0140)	(0.0190)	(0.0145)	(0.0200)
Startup based in CA	0.0434**	0.0230	-0.0528***	-0.0348**
	(0.0173)	(0.0153)	(0.0161)	(0.0158)
Startup based in MA	0.0384**	0.0261	-0.0686***	-0.0599***
	(0.0180)	(0.0195)	(0.0162)	(0.0218)
Startup based in NY	0.0462**	0.0513*	-0.0172	0.0207
	(0.0219)	(0.0309)	(0.0204)	(0.0320)
Observations	16940	8332	16940	8332
Number startups	8960	5617	8960	5617
Number VCs	2815	506	2815	506
R^2	0.00550	0.00590	0.0149	0.0137
Industry FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
VC firm FE?	Y	Y	Y	Y

Table IX—Portfolio management by VCs: valuations conditional on success

Notes: This table reports results from VC firm fixed effects regressions for two outcome variables. A unit of observation is a entrepreneurial firm financing associated with an investor. Columns (1) and (2) use log of the ratio of the valuation of the next equity financing divided by the first. Columns (3) and (4) use the log of the ratio of the final exit valuation (i.e. IPO valuation or acquisition price) to total capital invested in the firm at exit. VCs who are active (columns (2) and (4)) in the pre-period are defined as those investors with at least three investments prior to 2006. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year and "VC firm FE" are VC firm fixed effects. Standard errors are clustered by VC-firm are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Step up in valuation round 1 to round 2		Log exit value to capital raised (non-failed)	
	All VCs	"Active" VCs	All VCs	"Active" VCs
	(1)	(2)	(3)	(4)
Treated X Post-2005	0.195***	0.230**	0.217	0.355**
	(0.0722)	(0.0902)	(0.139)	(0.167)
Treated	-0.0408	-0.0657	0.239*	0.146
	(0.0452)	(0.0552)	(0.129)	(0.154)
Startup based in CA	0.125**	0.0400	-0.132*	-0.0740
	(0.0627)	(0.0636)	(0.0792)	(0.124)
Startup based in MA	-0.0448	-0.115	-0.238**	-0.184
	(0.0906)	(0.0818)	(0.108)	(0.148)
Startup based in NY	0.0235	-0.0181	-0.208*	-0.166
	(0.0703)	(0.111)	(0.119)	(0.236)
Observations	2442	1373	2488	1438
Number startups	1066	802	1133	832
Number VCs	806	343	837	368
R^2	0.0440	0.0535	0.0336	0.0409
Industry FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
VC firm FE?	Y	Y	Y	Y

Table X—Portfolio management by VCs: valuations conditional on success

Notes: This table reports results from the same analysis reported in Table IX but with the inclusion of triple interactions. "Young" is a dummy variable equal to one if the startup team's average age is less than the observed pre-2006 average. "No Serial" is one if none of the founding team members has previous founding experience. All other controls and fixed effects are as defined in the main specifications in Table IX. Standard errors are clustered by VC-firm are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Step up in valuation round 1 to round 2		Log exit value to capital raised (non-failed)	
	Founding team characteristics			
	Young vs. Old	Serial	Young vs. Old	Serial
	(1)	(2)	(3)	(4)
Treated X Post X Young	0.0802		0.222	
	(0.0824)		(0.205)	
Post-2005 X Young	-0.135		0.135	
	(0.0840)		(0.180)	
Young team	0.181***		0.0680	
	(0.0453)		(0.0969)	
Treated X Post X No serial		0.175**		0.258*
		(0.0762)		(0.153)
Post-2005 X No serial		-0.0939		-0.104
		(0.0719)		(0.128)
No serial entrepreneurs		0.0108		-0.0675
		(0.0322)		(0.0864)
Treated X Post-2005	0.160**	0.182***	-0.205	0.0324
	(0.0786)	(0.0648)	(0.159)	(0.123)
Treated	-0.0546	-0.0591	0.0943	0.298***
	(0.0429)	(0.0413)	(0.101)	(0.0902)
Observations	1807	2442	1916	2488
Number startups	800	1066	873	1133
Number VCs	642	806	705	837
R^2	0.0808	0.0610	0.0564	0.0453
Industry FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
VC firm FE?	Y	Y	Y	Y

Table XI—Log capital raised by five years after first VC

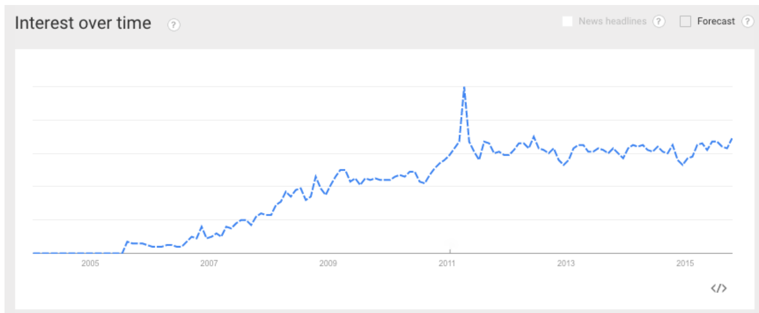
Notes: This table reports results from VC firm fixed effects regressions of the log of total capital raised by each year after the entrepreneurial firm's first financing event for firm's that survived at least 3 years. Column (1) effectively reports the main capital raised result of Table III. Column (2) measures capital stock as of two years later (similarly for the remaining columns). The sample considers only those investors that had investing activity before and after 2006. Industry fixed effects control for the five industry groups: Biotechnology and health-care, Business and financial services, Consumer goods and services, Energy and Industrials and Information Technology. "Treated" industries are defined at a more granular-level than these industry classifications so there is within-industry variation in startups that are defined as "treated" vs. not. "Year FE" indicate dummies for financing year and "VC firm FE" are VC firm fixed effects. Standard errors are clustered by VC-firm are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Total raised N years since first VC				
	1 year	2 years	3 years	4 years	5 years
	(1)	(2)	(3)	(4)	(5)
Treated X Post-2005	-0.225***	-0.102*	0.0114	0.00380	0.0361
	(0.0583)	(0.0562)	(0.0578)	(0.0617)	(0.0672)
Treated	-0.127***	-0.222***	-0.243***	-0.259***	-0.266***
	(0.0404)	(0.0419)	(0.0459)	(0.0482)	(0.0533)
Startup based in CA	0.148***	0.183***	0.240***	0.249***	0.323***
	(0.0404)	(0.0407)	(0.0441)	(0.0507)	(0.0541)
Startup based in MA	0.188***	0.214***	0.279***	0.320***	0.361***
	(0.0472)	(0.0511)	(0.0514)	(0.0560)	(0.0608)
Startup based in NY	-0.0276	0.0825	0.128*	0.191**	0.129
	(0.0686)	(0.0684)	(0.0772)	(0.0906)	(0.101)
Observations	7812	7256	6813	6274	5669
Number startups	5153	4769	4477	4130	3760
Number VCs	506	505	503	504	503
R^2	0.0281	0.0392	0.0456	0.0503	0.0550
VC firm FE?	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y
First round year FE?	Y	Y	Y	Y	Y

A. Appendix

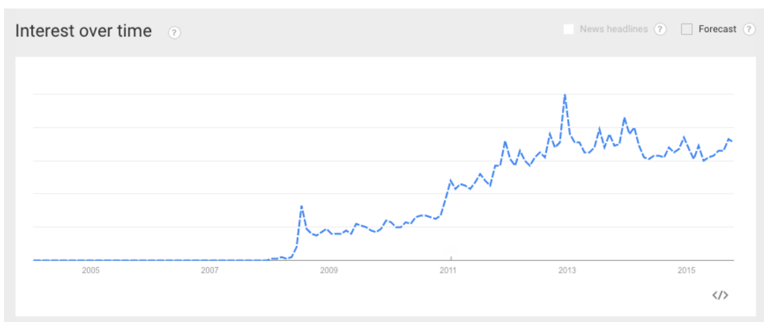
I. Tables and Figures

Figure A.I. Google trends data: Amazon EC2



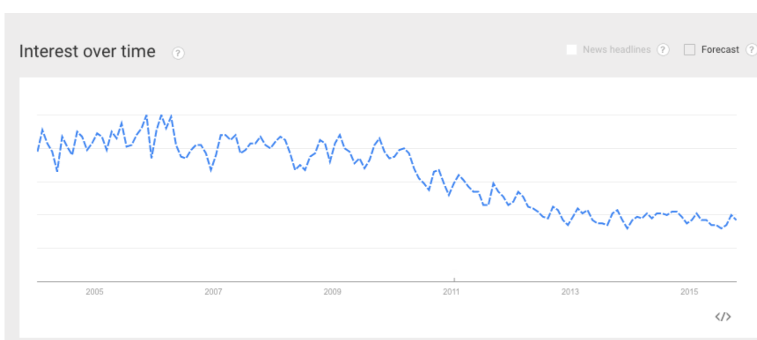
Notes: The figure presents the search term traffic for the phrase "Amazon Elastic Compute Cloud."

Figure A.II. Google trends data: App Store



Notes: The figure presents the search term traffic for the phrase "App Store," which is the marketplace for iPhone applications, a popular place for firms to sell their products.

Figure A.III. Google trends data: Open source software



Notes: The figure presents the search term traffic for the phrase "Open Source Software," which includes languages such as Python, Ruby and PHP.

Table A.I—Top words in company descriptions by industry classifications

Notes: Table reports the top 10 most common words in company descriptions in VentureSource by industry segment after excluding a list of common words. The excluded words beyond the standard common words such as "the" and "about" are: company, design, focus, industry, keywords, offer, product, provider and solutions.

Panel A: Treated Industry Segments	
Business Support Services	service, platform, online, management, data, marketing, advertising, technology, web, software
Consumer Information Services	online, users, web, service, platform, social, site, content, mobile, search
Financial Institutionsand Services	service, financial, payment, online, platform, credit, mobile, card, insurance, management
Media and Content	content, online, service, platform, web, media, video, news, learning, technology
Medical Software and Information Services	healthcare, management, service, health, software, medical, patient, care, information, data
Retailers	online, service, accessories, web, stores, customers, platform, apparel, site, retail
Software	software, service, management, data, platform, applications, mobile, technology, business, web
Travel and Leisure	travel, service, online, vacation, search, restaurants, platform, operator, web, users
Panel B: Non-Treated Industry Segments	
Aerospace and Defense	security, systems, video, surveillance, service, aircraft, military, system, technology, flight
Agriculture and Forestry	service, cleantech, water, agriculture, traits, food, plant, crop, irrigation, agricultural
Biopharmaceuticals	developer, treatment, drug, diseases, technology, disease, cancer, drugs, development, therapeutics
Communications and Networking	service, wireless, network, data, internet, applications, technology, networks, mobile, systems
Construction and Civil Engineering	service, cleantech, water, energy, waste, treatment, technology, environment, systems, management
Electronics and Computer Hardware	technology, storage, energy, systems, applications, data, developer, power, efficiency, devices
Food and Beverage	food, organic, tea, beverages, ingredients, natural, drinks, coffee, juice, foods
Healthcare Services	service, care, healthcare, health, management, medical, patients, treatment, centers, physicians
Household and Office Goods	water, energy, cleantech, efficiency, service, systems, home, led, consumer, lighting
Machinery and Industrial Goods	energy, technology, efficiency, cleantech, systems, applications, service, materials, industrial, system
Materials and Chemicals	materials, technology, cleantech, applications, developer, service, process, energy, water, coatings
Medical Devices and Equipment	developer, technology, devices, medical, treatment, device, system, patients, develops, patient
Non-Renewable Energy	gas, oil, natural, technology, service, cleantech, coal, exploration, power, energy
Personal Goods	skin, care, technology, accessories, online, performance, retailers, system, hair, service
Renewable Energy	solar, cleantech, energy, generation, technology, power, energyelectricity, fuels, developer, fuel
Semiconductors	technology, power, developer, semiconductor, applications, wireless, video, devices, integrated, digital
Utilities	energy, water, power, service, efficiency, cleantech, management, technology, treatment, customers
Vehicles and Parts	electric, vehicles, transportation, cleantech, service, systems, vehicle, energy, miles, drive
Wholesale Trade and Shipping	transportation, management, shipping, service, containers, container, freight, online,