The role of venture capitalists in the formation of new technological trajectories: Evidence from the Cloud

Completed Research Paper

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Abstract

We investigate the role of venture capitalists (VCs) in the creation of new technological ecosystems and in particular examine how VCs facilitate new ventures' product development decisions to use new technological platforms. Focusing on the recent rapid rise of a new computing paradigm, cloud computing, we develop and test a set of hypotheses based on a 1999-2009 sample of start-up firms that offer enterprise software products. We find evidence of strong complementarity between VC financing and the introduction of new products offered over the cloud. Moreover, the complementarity effects are significantly stronger for firms backed by VCs that had rich experience in the IT industry and are significantly weaker for firms that had prior experience developing traditional client/server products.

Keywords: Cloud computing, platform ecosystem, venture capital, complementarity

Introduction

Following the Schumpeterian insight that in order to bring innovations to the market there is a need for both ambitious entrepreneurs and adventurous financiers, the role of finance in the economics of innovation became an area of critical research (Schumpeter 1934, 1961). With Venture Capitalists (VCs) seen as an important entrepreneurial-financier in our age, research on VCs, their roles, rate of success, internal functions, and specific tasks in new businesses growth have seen significant advances in the last two decades. This research has led to a much deeper understanding of some aspects of the role of VCs and their business. We know quite a lot on how they are organized, the difference between different kinds of VCs, rates of return, impact on helping startups with professionalizing their internal human resources and financing operations, and critical role in creating and maintaining networks, to name just few areas (Da Rin et al 2011). A body of recent IS research has also begun to investigate the role of VCs, for example investigating how they affect product market competition in the IT industry (e.g., Kim et al. 2014), the interplay of product characteristics and geographic proximity between IT ventures and VCs (e.g., Greenwood et al. 2010), and the effect of social media platforms on new venture's VC financing opportunities (e.g., Aggarwal et al. 2012).

However, despite the widely held belief that VCs' active involvement in all aspects of their invested companies is what makes them unique compared with other private equity investments (Da Rin et al 2011), it might come as a shock to find out that we have very little systematic empirical evidence as to the role VCs play in technology development within their invested firms and the resulting paradigmatic shifts in technological trajectories. This is a crucial gap in our understanding. As a first step in advancing our knowledge in this key area, this study focuses on the role of VCs in the creation of new technological ecosystems and in particular examines how VCs facilitate new ventures' product development decision to use new technological platforms.

Our key argument is that because VCs could provide several benefits to their invested firms during the process of developing products using new technological platforms, they play an important coordination and instigation roles in the rapid diffusion of new platforms. In this way, they play a similar role to other "propagating institutions" such as R&D laboratories, government agencies, consulting firms, and user groups on the diffusion of new IT innovations that IS scholars have studied in the past (e.g., Fichman 2000, King et al. 1994).

We examine the salience of these arguments by developing and testing a set of hypotheses within the setting of the recent rapid rise of a new computing paradigm, cloud computing (hereby: cloud). We specifically explore whether VC financing is complementary to a start-up firm's decision to offer cloud products—i.e., whether the returns to software firms producing cloud products is greater in the presence of VC financing and vice-versa. Our focus on complementarities reflects the traditional challenges in VC research on identifying whether selection or treatment effects are behind the observed empirical relationships between VC financing and outcomes (e.g., Sørenson 2007). In our setting, we do not seek to identify between sorting and treatment explanations; indeed both may be present in the data and may play a role in facilitating the transition to a new platform.

Our approach to testing complementarities relies on revealed preference. Specifically, we use a firm's decision to offer cloud when funded by a VC as evidence that the returns to offering cloud are greater in the presence of VC financing, and vice-versa. Based on a 1999-2009 sample of start-up firms offering enterprise software products—one of the first crucial areas to utilize cloud computing, we find that receiving VC financing is associated with a 9.1 percentage point increase in the likelihood of launching a cloud product. We then demonstrate the robustness of our results using an alternative sample as well as an alternative empirical model. We next address potential omitted variable bias concerns by conducting instrumental variable estimation.

We further investigate the circumstances in which the complementarity between VC financing and cloud computing could be stronger and weaker. Our empirical results suggest that the complementarity effects are significantly stronger for firms backed by VCs that had rich experience in the IT industry and are significantly weaker for firms that already had significant experience in developing traditional client/server (C/S) products. These results are robust to alternative measures of the VCs' experience and a variety of specifications.

Theoretical Motivation

Challenges in developing products on new technological platforms

For a new technological ecosystem—that is paradigmatic shift in the ways core technologies are used—to occur, it is not enough for the technology to be developed, or even for a lead company to develop a product, but a whole array of products and functions on a systematic level have to occur in parallel (or at least in a short enough period) that companies would then switch to the new technology. For example, it was not enough for the personal computer to be invented, and for a significant competition to develop between various PC makers.[1] Only after a whole ecosystem of software, services, data-communication, and skills evolved around the specific Windows-Intel (also known as Wintel) platform, then companies shifted their computing paradigm away from mainframe, mini, and workstation and toward the PC and its client-server architecture.

While it is tempting for start-up firms to develop new product using an emerging technological platform, there are several challenges that may prevent the firms from doing so. The first challenge of forming a new technological ecosystem is coordinated instigation. Enough actors need to be reassured that other actors are working on the different necessary aspects of the technological-business problem so that when they come up with their specific solution, it would be viable both technologically and in the market. Otherwise it would be irrational for them to invest in its research and development. In more established fields, public or public-private solutions for the coordinated instigation problem exist. The most widely cited of these solutions is the semiconductors technology development map, which ensured a widespread agreement on goals, standards and timeframes and stimulated investment from a wide array of actors spread around the globe to come forth and achieve its stated goals of technological development. However, in cases of unproven new technologies, where markets do not exist, and no one is quite sure what the new technologies are supposed to perform and what are (if any) the profitable business models, there is no established private-public mechanism to play that coordination role.

Meanwhile, to develop new products using an unproven technological platform, various problems need to be tackled by the firms themselves, as there is no prior experience or know-how to learn from (Greenstein 2000). Only firms with the best technical team could have the ability to encounter all difficulties and take the lead on the new technological trajectory.

Yet, even the start-up firms with the best quality may incur substantial costs and risks when launching new products based upon an emerging platform. The first are learning and search costs associated with developing products compatible with the new platform. Because the ways core technologies are used may be completely different from the old platform, the start-up firms would need to develop new technical components or change the old designs completely. This problem becomes more acute if there are some missing components the start-ups need to license from others, a common phenomenon for industries featured with overlapping intellectual property rights (e.g., Cockburn and MacGarvie 2009). The potentially high licensing and transaction costs may prevent the firms from entering into markets using the new platform in the first place. Second, commercializing new products on an unproven platform may be costly and risky, and is likely to involve *economic experiments* to understand how opportunities enabled by the new platform can be translated into feasible business models (e.g., Rosenberg 1992).

As an example, consider the recent shift from the C/S computing paradigm to cloud computing: in order to launch a software-as-a-service product to the market, the start-up firms not only need to identify new business models and sort out licensing and legal issues, but also need to take tremendous efforts to re-organize the entire organization (e.g., cutting the technical teams that are supposed to provide on-site services under the traditional C/S model) and spend a fortune to advocate the new technology to the market. For instance, to promote its on-demand CRM product, Salesforce.com spends roughly 50% of its yearly revenues on marketing expenses, resulting in a thin profit margin.

It is worth noting that the above discussions are not intended to provide a comprehensive list of challenges that the start-up firms could face when developing new products on an unproven technological platform. Here we focus on just some of the more common problems that could be potentially addressed by the VCs. Our next section will therefore discuss the roles of VCs in addressing these challenges.

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[1] The "prominence" of the IBM PC is now so etched into our public mythology that a little known fact is that the bestselling home computer of all time was actually the Commodore 64, which outperformed IBM PC and its clones in the global market until 1988.

The role of VCs in complementing firm's product development on new technological platforms

VC firms (or funds) are organized as partnerships between General Partners (GPs) and Limited Partners (LPs). GPs are a small set of individuals who make the investment choices and who assert active management and are involved in several of the companies the fund invested in. LPs are a set of institutional and/or rich individuals who passively invest in a VC fund (usually active for ten years) who supply the capital. The GPs are the individuals whose profession is being the venture capitalists. The GPs make their money in the form of management fees and carry (performance based fees), the LPs make (or lose) their money when the VC fund distributes the returns after successful exits (that is either IPO or M&A). The ability of GPs to stay in business relies on their capability to raise successful funds on a regular basis, which in turns relies on their ability to supply the LPs with reasonable return on investment via successful financial exits. Notice that this model means that, unlike the popular media description of VC as long-term investment, the VCs usually aim to perform a financial exit within five years of investing in a company.

The literature has suggested the following several roles played by VCs. First, it has been argued that VCs are able to screen and identify better quality ideas and firms. Chemmanur et al. (2011) show evidence that the efficiency of VC-backed firms before receiving VC fund is even higher than that of non-VC-backed firms, suggesting the screening role played by VCs. Regarding their role particularly in picking firms with the best innovations, Hellmann and Puri (2000) show that companies that are following innovator strategies are more likely to get VC funding than these that pursue imitation. Indeed, when we interviewed a prominent Silicon Valley VC for the project we were told: "*We at <name of fund> have made specific investments so we are allowed into the best labs in Stanford and Berkeley and employ enough researchers as consultant to be able to know of new technological trends as soon as they appear. We find this very worthwhile over the years leading to some of our best "hits*." Therefore, we argue that because VCs tend to develop various techniques with which to keep abreast of new trends and technologies, they could act as a catalyst to the shift into a new technological platform by aggressively selecting the best firms and betting on them early. By doing so the VC industry mobilizes enough capital around new technological trajectories to sponsor the creation of a vibrant ecosystem that makes the switch to new technologies sensible from the point of view of customers and consumers.

VCs also play an important role as information intermediaries (e.g., Hsu 2006) for their invested firms. Because of their strong network of information and contacts, the VCs could provide private information access and reduce search costs for their invested firms, and they could also be more aware of the potential opportunities and threats than internal directors of the firms (Gans et al. 2002, Hsu 2006). In our setting, this function could significantly help the start-ups efficiently learn and develop new products that fit with the new platform. In addition to the information intermediation, when start-ups need to negotiate certain missing components from external actors, VCs could potentially serve as bargaining intermediaries to facilitate the transactions (Gans et al. 2002). In sum, these discussions suggest the important influence by VCs in reducing a variety of costs associated with developing products on a new platform.

A body of studies has investigated the effects of active management exerted by VCs on the value of the firms. Besides monitoring the invested firms (e.g., Lerner 1995), VCs also play an important role in building the internal organization, formulating human resource policies, or hiring VP of sales and marketing (Hellmann and Puri 2002). We argue all these extra-financial value-added services could effectively assist the firms to sort through all the issues discussed above related to commercializing the products based on new platform.

All the foregoing discussions suggest the significant role of VCs in addressing the challenges of developing products on an unproven platform. They motivate our argument that because VCs increase the net benefits from developing new products on an emerging platform, all else equal, we would expect a strong complementarity between VC financing and launching products on a new technological platform.

Both theory and some findings (e.g., Bottazzi et al. 2008, Gompers et al. 2009) suggest that the more experienced are the VCs as technologists and entrepreneurs, the better they are in performing the functions described above, including selecting the best ideas and firms, mitigating costs involved with new product development, as well as providing active management guidance. As a result, we expect the complementarity between VC financing and launching product on a new platform will be stronger when VCs have gained a rich experience in the focal industry.

Last, some start-ups may already have experience in developing products for a prior platform. The informational benefits of VCs may be lower for such firms, leading to a weaker complementarity. There may be several reasons for this. First, to the extent such firms may have already invested significant sunk costs in developing products under the old platform, there may be lower net benefits for developing products for the new platform. This will be particularly true in environments where lessons learned on one platform may not easily be transferred to the new environment (e.g., Davis et al. 2014), as may be the case with cloud computing. For example, the firm may have developed technical capabilities around delivering products and services in the old platform. It may have also developed an understanding of business models that may work under the old platform; such as a service and support model whose economics may be well suited to traditional C/S products. If these capabilities are not well situated to the new environment then VC financing may not have as great an impact on how products and services are delivered (e.g., Penrose 2009). Further, some prior literature has argued that firms' existing capabilities make themselves difficult to adapt to new circumstances (e.g., Nelson and Winter 1982; Teece et al. 1997; Tripsas and Gavetti 2000). In our environment, prior experience with the old platform could create inertia that is difficult to overcome, even with access to new information from the VC.

To investigate these hypothesized influences of VCs, we look at the early stages of a new paradigmatic technological shift, i.e. the period before the technology acceptance curve took off and the emergence of an ecosystem of complementary institutions and services. We focus on the recent movement from traditional C/S computing to the cloud. Cloud computing is now widely accepted as the new paradigm of computing that slowly revolutionizes the ways in which computing is used, and by whom, throughout all sectors of the economy. However, in order to realize its promise it was not enough that it was just offered as an infrastructure, for example, software or storage as a service, but a whole ecosystem of how computing is organized, and how software and equipment are developed. Business models have had to be developed at more or less the same time in order for the option to move to cloud would make sense on large scale. Accordingly, it supplies a rich case with which to check how VCs influenced firm decisions on developing products based on the new, yet-to-be-proven paradigm. Based on our discussions above, we immediately have the following three testable hypotheses in this context:

Hypothesis 1 – VC financing is associated with an increase in the likelihood of initial cloud product launch by a start-up firm.

Hypothesis 2 – VC financing is associated with a greater increase in the likelihood of initial cloud product launch when the VC has rich experience in IT industry.

Hypothesis 3 –VC financing is associated with a smaller increase in the likelihood of initial cloud product launch for a start-up firm that has rich product experience.

Empirical framework

In short, we argue that VC financing is complementary to the introduction of new products offered over the cloud; that is, the returns to VC financing for start-up firms will be greater when the start-up offers cloud products, and vice-versa (e.g., Brynjolfsson and Milgron 2013). Our approach to testing for complementarities between VC financing and cloud relies on revealed preferences. We follow the empirical approach of Novak and Stern (2009). Suppose there is an observable binary status on whether a firm launches its initial cloud product, denoted as k = *Initial cloud product launch*, with net benefits to the firm denoted by β_k. Both the firm i and the econometrician observe a vector of decision-specific drivers Z_{ki} with marginal returns to the firm as δ_k. There are also some decision-specific mean-zero shocks η_{ki}, which are observed by the firm but not the econometrician, and can be composed into ξ_i (i.e. firm-level shock for firm i) and ε_{ki} (i.e. some shock particularly related to firm i's cloud product launch decision).

Assume firms will launch the cloud when the net benefits to this decision are positive. Given the discussions above on how VC increases the net benefits from developing cloud product, the marginal returns to cloud product launch also depend upon the existence of VC financing. Therefore, we have:

Initial cloud product launch $_i = 1$ if $\lambda VC_i + \beta_k + \delta_k Z_{ki} + \xi_i + \varepsilon_{ki} > 0$, where k= *Initial cloud product launch*. (1)

In equation (1), λ captures the benefits from *VC* (an observable binary status on whether the firm has successfully attracted VC financing) to the marginal returns to cloud product launch. Our main objective of the empirical analysis is to determine whether λ is greater than zero. If we convert equation (2) to a linear probability model, it can be written as follows:

Initial cloud product launch $_i = \lambda VC_i + \delta_k Z_{ki} + \eta_{ki}$, where k= *Initial cloud product launch*. (2)

Because the firm-level shock ξ_i is included in η_{ki}, a cross-sectional estimation using ordinary least squares (OLS) will lead to a biased estimate of λ, since ξ_i might be also correlated with VC financing (i.e. VC_i). For example, a positive λ may not be caused by the complementarity between the two; instead, it might occur if a firm with an excellent team of internal directors would tend to attract VC financing as well as launching product based on the new cloud platform. To address this concern, we construct a panel and employ a fixed-effect linear probability model to eliminate any firm-level time-invariant unobservables that could correlate with both the status of receiving VC financing and the status of launching cloud product. More specifically, if we suppress the *k* subscript on our parameters in equation (2) to simplify notation, the baseline empirical model based on panel data can be written as:

Initial cloud product launch $_{it} = \lambda VC_{it} + \delta Z_{it} + \mu_i + \tau_t + \eta_{it}$ (3)

Initial cloud product launch $_{it}$ is a binary variable that is equal to 1 if firm i launches its first cloud product in year t and is equal to 0 otherwise; VC_{it} is also a binary variable, which is equal to 1 if firm i has received VC by year t and 0 otherwise. The parameter λ captures the complementarity and our interest is to test whether $\lambda>0$. Z_{it} is a set of control variables that vary by firm and by year and could potentially influence firm's decision to launch cloud product. μ_i represents the time-invariant unobserved firm heterogeneity and τ_t is the full set of time dummies that control for general time trends that may be correlated with both the chance of receiving VC and the likelihood of launching cloud.

Nevertheless, one could still argue that some time-varying components in η_{it}, which are not observed by the econometrician, may be correlated with both the firm's status of receiving VC financing and launching a cloud product. As shown below, we employ instrumental variable regressions to address this concern.

Data and Measures

Sample

We created a sample of start-up firms that offer enterprise software products—one of the first crucial areas of computing to utilize cloud computing, and in particular the software-as-a-service model[2]. We focus on enterprise software to reduce the extent of unobserved heterogeneity in our sample, as both the incidence of VC funding and the cloud business model may be influenced by many unobserved factors. Further, some of the most popular early providers of cloud application services operated in enterprise software, such as Salesforce.com. Last, and related, in contrast to many consumer software apps that were built specifically to offer services over the Internet—such as some of Google's applications—because many enterprise software firms are operating on client data they faced a clear choice between developing cloud solutions and offering traditional C/S products. The sample firms come from the 2003, 2004, and 2010 editions of CorpTech Directory of Technology Firms (denoted as CorpTech hereafter) with primary SIC code as 7372. Based on the product categories defined by CorpTech, we selected the firms that produce enterprise applications such as accounting, business planning, banking, manufacturing, sales and marketing, warehousing and distribution applications.[3] Our sample begins in 1999 (the last year in which the concept cloud computing was not yet formed) to 2009, a year by which every start-up formed should have been exposed to the idea of offering cloud products as the term became ubiquitous and widely accepted as the new and upcoming computing platform.

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[2] That is, give our focus on software firms, the terms "cloud product" and "software-as-a-service" are interchangeable.
[3] There are more than 290 software product codes (denoted as SOF) defined by CorpTech Directory. Each firm in this directory is associated with a set of self-reported product codes selected from these 290 SOF categories.

While our CorpTech data has detailed information on the product market segments of firms, it does not vary over time from year 2005 to 2009. Therefore, we combine the data extracted from CorpTech with the data from the National Establishment Time Series (NETS) Database, which includes 100,000 U.S.-based firms primarily in SIC 7372 and provides longitudinal information over 1990-2009 on sales, employment, location, and other basic variables. In order to focus on start-up firms only, we restrict the sample to firms that were founded after 1990 and that have fewer than 1000 employees and less than $500 million annual sales, which gives us 339 firms in total.

Variables

Dependent variable: Initial cloud product launch

This variable captures whether a start-up firm i launched its first cloud product in year t. To identify initial cloud product launch event, we took each firm's name and searched for its press releases in the PROMT database, as has been done previously in the literature (Fosfuri et al. 2008). Then, we employed a combination of automatic search and manual reading to identify the sample firms' product introduction events. Third, we followed the definition of cloud computing by Kushida et al. (2010) and derived a set of keywords related to cloud in the software-as-a-service (SaaS) category, as our sample firms primarily produce enterprise software products. These keywords not only include more generic ones such as cloud, cloud computing, and software-as-a-service, but also include phrases describing the features of cloud computing business model, such as on-demand, pay-as-you-go, and subscription-basis. We then used a text mining tool and searched for these keywords in the set of new product introduction articles. Lastly, we manually read all search results to ensure we have correctly identified cloud product introductions. In total, among the 339 sample firms, we found 52 firms that introduced cloud products over our sample period.

Because we are interested in the role of VCs in promoting cloud computing ahead of the technology acceptance curve (i.e. the period prior to widespread acceptance of cloud computing), the focus of our empirical analysis is on the initial cloud product launch. Therefore, we dropped all observations for a firm once it introduced its first cloud product, as the firm is no longer exposed to the hazard of offering an initial cloud product. Moreover, among the 339 sample firms, we find 72 firms that received VC before our first sample year (i.e. 1999). Because we are particularly interested in investigating how the change in VC-funding status complements the decision to launch cloud products, we construct our baseline sample by dropping these 72 firms. However, as discussed below, we test the robustness of our results by using the full sample. In summary, our baseline sample consists of an unbalanced panel with 2325 observations by 267 firms from 1999 to 2009. Table 1 includes summary statistics for the main variables used in the empirical analysis over our entire sample period.

	Baseline sample				Sample of firms that launched cloud				Sample of firms that did not launch cloud				Difference (t-statistics)
Variable names	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Launch cloud vs. Not
Initial cloud product launch	.018	.133	0	1									
VC	.208	.406	0	1	.409	.493	0	1	.187	.390	0	1	7.835***
VC's prior 5-year experience	2.634	8.835	0	66	11.357	19.329	0	66	1.722	6.208	0	37	16.237***
product experience	5.107	11.513	0	110	6.336	9.604	0	65	4.978	11.689	0	110	1.666**
Sales	4.081	11.879	0	231	7.179	13.838	0	111.29	3.757	11.611	0	231	4.079***
Downstream capabilities	.003	.009	0	.219	.001	.003	0	.037	.003	.010	0	.219	-1.931**
Innovations	.012	.067	0	.970	.006	.030	0	.303	.012	.070	0	.97	-1.300*
Age	8.421	4.811	1	20	6.991	3.951	1	17	8.570	4.869	1	20	-4.653***

Note: 1) the baseline sample includes 2325 observations by 267 firms; the sample of firms that launched cloud includes 220 observations by 42 firms; the sample of firms that did not launch cloud includes 2105 observations by 225 firms. 2) * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1. Summary Statistics

Independent variables

VC. This variable indicates if a firm i had received any VC financing by year t. We followed a large body of literature (e.g., Chemmanur et al. 2011, Tian 2011) and use the VentureXpert database by Thomson

Financial Corporation as the primary data source for this variable. VentureXpert provides detailed round-by-round information for firms that VCs invest in, including the date for each round of investment, round number, round amount, syndicating VCs, and the total investment amount by each VC. We matched our sample firms with firms in VentureXpert and found 145 firms had received VC funding by 2009, including 72 firms that received VC funding before 1999. Following the literature (e.g., Hsu 2006), we consider receiving VC as an absorbing state. Therefore, if a firm i received the first round VC funding in year t, the variable VC will take the value of 1 in year t and all following years, and otherwise it will be equal to 0.

VC experience. For a VC-backed firm i, this variable refers to the lead VC's IT-related experience. To avoid potential endogeneity, we focus on the pre-sample VC experience. We use the lead VC's prior 5-year experience (denoted as VC's prior 5-year experience) as the baseline measure, as we believe using the prior 5-year window reflects VC's most recent investment focus and expertise. However, we also use the lead VC's prior 10-year experience (denoted as VC's prior 10-year experience) as a robustness check. The measure of lead VC's IT-related experience is computed in three steps. First, to identify the lead VC for a VC-backed firm in our sample, we follow the existing literature (e.g., Tian 2011) and consider the VC that provided the greatest investment across all rounds and that participated in the first round funding as the lead VC. Second, we extracted all VC funding activities in portfolio companies operating in the information technology (IT) industry from VentureXpert, and then for each VC, we counted the number of IT firms in which the VC invested as the first round investor from 1994 to 1998 as a measure of the VC's prior 5-year experience (we used investments from 1989 to 1998 as a measure of the VC's prior 10-year experience). Third, we matched the VCs (from the second step) with lead VCs that invested in our sample firm (from the first step) so that we know for each VC-backed sample firm, its lead VC's experience in the IT industry as early-stage investor. For firms backed by multiple lead VCs, we use the average experience.[4]

Product experience. This variable captures the focal firm i's experience in producing traditional C/S software products by year t and is measured by the cumulative count of C/S products introduced by firm i from year 1999 to year t. We use a two-step procedure to identify the introduction of C/S products based on the press releases in the PROMT database. First, we manually read all the news articles by the 339 sample firms and identify new software product introductions. Second, we define a new software product introduction event as a C/S product introduction as long as it does not include any keywords related to cloud as described above. Given the data limitation that we only obtained product introduction events after 1999, we acknowledge that using the count of C/S products introduced from 1999 to year t is an imprecise measure for a firm's total C/S products cumulated to year t. However, as detailed below, the employment of fixed-effect model will control for any time-invariant effect that differs across firms, including the pre-sample C/S product count.

Control variables

Downstream capabilities. As has been suggested by Fosfuri et al. (2008), when a firm invested heavily in its marketing efforts, brands, and distribution channels, the firm is less likely to introduce new products because of a fear of eroding profits in existing business. Meanwhile, a firm's downstream capabilities will also be likely to correlate with the opportunity of VC funding. To control for this effect, following prior literature (e.g., Huang et al. 2013), we extract trademark data from USPTO and use the count of live trademarks (in thousands) held by firm i up to year t as a measure of the firm's downstream capabilities.

Innovations. Prior literature (e.g., Mann and Sager 2007) has highlighted that VCs tend to fund firms with demonstrated innovation capabilities. On the other hand, a highly innovative firm will be more likely to enter into new technology paradigms such as cloud computing. In line with the existing literature that studies the relation of VC to firm innovation output (e.g., Kortum and Lerner 2000), we use patents as a measure of firm's innovation output and add it as a control in the empirical analysis. For a firm i, we obtained its granted patents as well as patent applications cumulated up to year t from the NBER Patent Data Project and USPTO website. We use claims-weighted counts (in thousand) of granted patents for firm i up to year t as the baseline measure, as it is the patent's claims that determine the economic value of

[4] We checked the robustness of our results by using the total (instead of the average) experience if a sample firm has multiple lead VCs. The results are very consistent and available upon request.

a patent. We further use the raw count of granted patents, the claims-weighted count of patent applications, and raw count of patent applications for firm i up to year t as robustness check, which gives us consistent results.

Other controls. To control for firm size-related effects that could influence both the chance of receiving VC funding and the likelihood of launching cloud products, we obtain the longitudinal sales (in million) data during the 1999-2009 period from the NETS Database as a measure of firm size (denoted as *sales*). We also examine the robustness of our results by using the number of employees as an alternative measure, the data of which is also directly obtained from the NETS database. The results are consistent with using sales as a control.[5] As has been discussed elsewhere, firm age is also an important factor that affects both a firm's financing opportunity and the firm's product strategies. Unfortunately, because firm age is highly collinear with the full set of yearly dummies used to control for year-fixed effects, we were unable to add firm age as a control in the fixed effect linear probability model, but it is included when we test the robustness of the results using Cox proportional hazard model.

Empirical Results

Our empirical analysis proceeds in several steps. First, we investigate the role of VC in complementing a firm's cloud product launch decision using the above baseline empirical framework. Then, we test the robustness of the results through a different sampling strategy and an alternative empirical model. We further try to address omitted variable bias by employing instrumental variable estimation. We then demonstrate how the influence by VC is shaped by VC's past experience in IT industry and the start-up firm's existing product experience, and whether these results are consistent to alternative measure and specifications.

Baseline results and robustness tests

Figure 1 presents a time-series chart of the cumulative percentage of the sample firms that launched initial cloud products, for VC-backed versus non VC-backed firms. Overall, while firms rarely entered into cloud computing business before 2002, there is a significant rise from 2003 to 2006, however the rate of increase slows after 2006. Moreover, there is a significant difference in the percentage and speed of cloud product launch between VC-backed and non-VC firms.

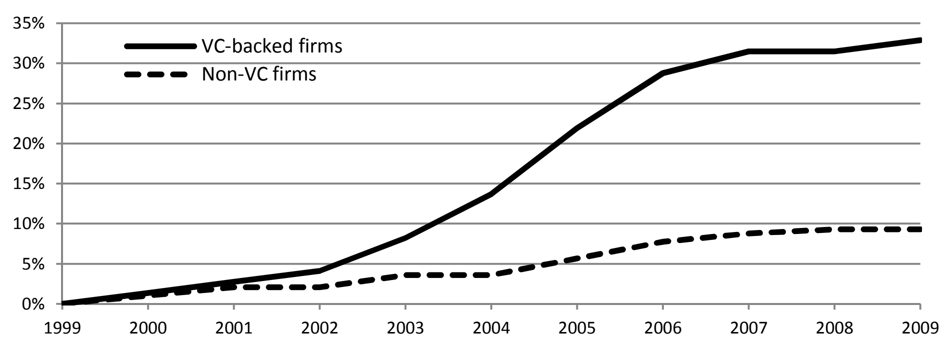

Figure 1: Cumulative percentage of firms introducing cloud product, VC-backed firms vs. Non-VC firms

Besides presenting the summary statistics of our major variables using the full sample, in table 1, we also slice the sample into a subsample of firms that offer the cloud versus a subsample that does not, and conduct a non-parametric test of the difference of these variables between the two subsamples. As shown in table 1, for sample firms that launch cloud products, they are more likely to be funded by VCs and their VCs seem to exhibit greater level of IT-related experience than sample firms that do not launch cloud products. Further, firms who release cloud products have a greater level of product experience and have

[5] We did not use both sales and employment as controls for firm size, as these two variables are highly correlated.

greater sales volume. On the other hand, the firms that do not launch cloud seem to have greater downstream capabilities (as proxied by the number of live trademarks), have filed more patents, and are older.

In columns (1) and (2) in table 2, we use the regression model in equation (3) to explore the basic relationship between VC and a firm's cloud launch decision. Column (1) shows the relationship between *VC* and *Initial cloud product launch* with only sales as a control. We include *sales* in all regressions because it may affect a firm's likelihood of receiving VC funding as well as its likelihood of launching a cloud product. The coefficient on *VC* is .091, suggesting that receiving VC financing is associated with a 9.1 percentage point increase in the likelihood of launching cloud product. Column (2) employs the full set of our baseline controls, and the results are very similar to column (1).

As discussed earlier, our baseline sample drops the firms that received VC funding before the sample period (i.e. before 1999). However, it would be interesting to test the robustness of our results by incorporating those dropped firms. The results using the full sample are reported in columns (3) and (4) in table 2, which remains consistent to the baseline results.

We choose linear probability model as our baseline specification because it enables us to employ a firm-level fixed effects to control for time-variant unobservables. The interpretation of the implied marginal effects is also easier in this model. As an additional robustness check, we employ hazard models as an alternative specification, as it is in particular useful to model the risk of events occuring at time t, given the subject has survived until time t. More specifically, we choose the Cox proportional hazard model, as it is a semi-parametric model that makes no assumption on the shape of the baseline hazard over time and assumes that covariates are multiplicatively related to the hazard. In our setting, suppose $h_i(t|X_{it}) = h_o(t)*\exp(X_{it}'\beta)$, where $h_i(t|X_{it})$ is the conditional instantaneous hazard rate for firm i in year t to launch cloud products. $h_o(t)$ is the unspecified baseline hazard in year t, and $X_{it}'\beta = \beta_1 VC_{it} + \beta_2 Sales_{it} + \beta_3 \text{Downstream capabilities}_{it} + \beta_4 Innovations_{it} + \beta_5 Age_{it} + \tau_t$.

The results based on the Cox proportional hazard model are presented in columns (5) and (6) in table 2. The estimated coefficients suggest that once a firm received VC funding (i.e. the variable *VC* has a discrete change from 0 to 1), the firm exhibit a 144% increase in the hazard rate of launching cloud product.

Dependent variable: Initial cloud product launch	Baseline sample, OLS		Full sample, OLS		Baseline sample, Cox proportional hazard models	
	(1)	(2)	(3)	(4)	(5)	(6)
VC	.091*** (.034)	.091*** (.034)	.090*** (.034)	.090*** (.034)	1.440*** (.343)	1.443*** (.342)
Sales	.001* (.001)	.001* (.001)	.001 (.001)	.001 (.001)	.015** (.006)	.015** (.006)
Downstream capabilities		.034 (.008)		.024 (.248)		-27.682 (31.869)
Innovations		.029 (.093)		-.010 (.010)		-.621 (2.540)
Age					.021 (.051)	.020 (.051)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	No	No
Number of firms	267	267	339	339	260	260
Number of observations	2325	2325	3004	3004	2058	2058

Notes: 1) Heteroskedasticity robust standard errors clustered over firms are in parentheses. 2) * significant at 10%, ** significant at 5%, *** significant at 1%. 3) Although the coefficient and the robust standard error of *Sales* look the same across specifications, it is because we round up the robust standard error to 3-digit. The robust standard error of *Sales* is mostly around .0005, and the coefficient of Sales is mostly significantly positive at 10%.

Table 2: The complementarity between VC financing and cloud product launch

Addressing omitted variable bias

Although the fixed effect linear probability model in the previous section addresses time-invariant unobserved heterogeneity across firms, one important concern is that some time-varying omitted variables may correlate with both a firm's tendency to launch cloud and its opportunity to obtain VC funding, leading to a biased estimate of the variable *VC*. Therefore, we take the following steps to conduct an instrumental variable estimation.

Our first step is to identify variables that are likely correlated with a firm's likelihood to receive VC but is uncorrelated with firm-level unobservables such as new product development strategy. Following Chemmanur et al. (2011), our first variable is the number of limited partners that invested in VC funds existing over the prior 5-year rolling window and located in the same state as the sample company. This variable is correlated with the likelihood that a company will receive VC funding but is unlikely to be correlated with a company's product strategy, as limited partners usually don't interact with portfolio companies directly. Using limited partners in the same state is based on the assumption that, as articulated by Chemmanur et al. (2011), the greater the number of limited partners in geographic proximity to the sample firms, the more likely for the local VCs to raise funds, and therefore the greater chance for the firms to be backed by VC.

Second, as Hochberg and Rauh (2012) suggested, different types of institutional investors may exhibit different tendencies to invest locally. Public pension funds may in particular show home bias. Therefore, our second variable is the number of public pension funds that invested in VC funds over the prior 5-year rolling window and located in the same state as the sample company.

Third, in line with the approach taken by Kolev (2013), the third variable is the total dollar value of VC-backed initial public offerings (IPOs) in all non-IT industries in the prior 2 years and in the same state as the sample company. The logic of using this variable is discussed in great detail in Kolev (2013). In short, first, given the usual venture capital cycle,[6] there is a significant correlation between the IPOs in the previous cycle and the supply of VC funding into new ventures in the next cycle. Therefore, the more IPOs in prior years, the more likely it is that our sample firms will receive VC funding in the current period. We measure the prior two years of IPOs because, as argued by Kolev (2013), it provides the strongest power in predicting future investment. Meanwhile, because IPOs are usually driven by financial market conditions, they should not influence a firm's product development strategy. To further rule out any possible correlation between IPOs and our dependent variable, we only focus on the IPOs realized in non-IT industries. The focus on IPOs in the same state is in the same spirit as the above first instrument, i.e. the home bias exhibited by the supply of VC funds. Following a similar logic, for our fourth instrument we also identify the total number of mergers and acquisitions (M&As)[7] in all non-IT industries in the prior 2 years and in the same state.

Last, we use a dummy measure for these four variables (i.e. taking a value of 1 if it is above 50th percentile and otherwise 0), as this is a straightforward way to incorporate nonlinearities of their effects on VC funding. We further interact each of them with a linear time trend (denoted as *High limited partners X time trend*, *High public pension funds X time trend*, *High IPOs X time trend*, and *High M&As X time trend*), because their results are likely to vary over time.

Following prior literature (Angrist and Pischke 2009), our second step is to employ a probit model to predict the likelihood a firm receives VC funding by using these four variables as the predictors. The results are reported in column (1) in table 3. The number of limited partners and the number of M&As seem to strongly and positively predict the chance to get VC funding, though we do not find a similar effect from public pension funds and IPOs.

The next step is use the predicted likelihood of receiving VC funding from this probability model in column (1) as the instrument. Because all of the above four factors should not be correlated with firm-level unobservables that might affect product development decisions, this predicted value should not be correlated with these unobservables either. Using nonlinear fitted values of instruments in this way has been shown to have greater efficiency than a traditional linear first stage but still provide consistent estimates (Angrist 2001, Newey 1990). We then estimate a fixed effects linear probability model with instrumental variables and report the results from the two stages in columns (2) and (3) in table 3 respectively. As expected, in the first stage, the predicted value of the likelihood of receiving VC financing

[6] The venture capital cycle refers to the cycle that starts with the funding of new ventures, continues onto developing those new ventures into mature firms, and then the exit through IPOs or acquisitions. It closes with the VC re-investing into new ventures.

[7] Unfortunately, most of M&As in our dataset have missing transaction values, so we are only able to compute the number of M&As instead of the dollar value of M&As.

based on the above four factors are strongly correlated with a firm's true VC funding status. The F-statistic is 18.16, above the commonly used threshold of 10 and also above the Stock-Yogo (2005) critical threshold for weak instruments. The results from the second stage show the sign of the coefficient of *VC* variable is consistent with the baseline result, though the magnitude and standard error are somewhat greater. In sum, this set of results using instrumental variable provide us additional confidence that our results were not driven by omitted factors.

	Probit model with DV as whether firm i in year t had received VC	Fixed effects linear probability model with instrumental variable			
		First stage		Second stage	
	(1)		(2)		(3)
High limited partners X time trend	.097*** (.021)	Predicted probability of receiving VC funding	.321*** (.075)	VC	.315* (.172)
High public pension funds X time trend	-.031 (.020)	Sales	-.001 (.001)	Sales	.001* (.001)
High IPOs X time trend	-.006 (.014)	Downstream capabilities	.110 (.292)	Downstream capabilities	.008 (.205)
High M&As X time trend	.045*** (.013)	Innovations	-.014 (.116)	Innovations	.014 (.077)
Year dummies	Yes	Year dummies	Yes	Year dummies	Yes
Firm fixed effect	No	Firm fixed effect	Yes	Firm fixed effect	Yes
F-statistic			18.16		--
Stock-Yogo (2005) critical value (10% maximal IV size)			16.38		--

Notes: 1) Heteroskedasticity robust standard errors clustered over firms are in parentheses. 2) * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: The complementarity between VC financing and cloud product launch, instrumental variable estimates

Examining when the complementarity is stronger or weaker

We have examined the average effect of VC in complementing a firm's new product development decision (i.e. launch cloud product in our setting). In this section, we investigate the circumstances under which such complementarity is likely to be stronger or weaker. Our hypothesis suggests the complementarity is stronger when a firm is backed by a VC that has rich experience in IT industry. We test this hypothesis by adding the interaction between VC and VC experience to the regression model. As shown in column (1) in table 4, the estimated marginal effects suggest that firms backed by VC that has little experience in IT industry are associated with a 5.4 percentage point increase in the likelihood of launching cloud product, and this effect is statistically insignificant. On the other hand, firms backed by VC that has rich experience in IT industry are associated with a statistically significant 7.4 percentage point increase in the likelihood of launching cloud product. As implied by the coefficient of the interaction term, the two marginal effects (at the 10th and 90th percentiles of VC experience) are statistically significant. We then examine the robustness of the results by measuring VC experience using prior-10 year experience, and the results are very consistent, as shown in column (2) in table 4. These results provide strong evidence on the important role of VCs' experience on its influence on the product development trajectory of their invested companies.

We next explore how a firm's existing product experience shapes the complementarity between VC and a firm's product development decision. We add the interaction between VC and a firm's product experience to our baseline model. As reported in column (3) in table 4, receiving VC funding is associated with a 11.5 percentage point increase in the likelihood of launching cloud for firms that have low product experience but is only associated with a 8.6 percentage point increase for firms that have rich product experience. The coefficient on the interaction term suggests a statistically significant difference between low and high product experience.

However, start-ups with low product experience also imply they are younger, so one explanation on the stronger effect of VC on a firm with little product experience is that this type of firm is likely to be younger and thus requires VC's greater intervention. To disentangle this age effect from product experience effect, we add the interaction between firm age and VC (denoted as *VC x firm age*) to the regression model. The results are reported in column (4) in table 4. The coefficient on *VC x product experience* remains significantly negative.

Dependent variable: Initial cloud product launch	VC's prior 5-year experience	VC's prior 10-year experience	no lagged *product experience*		1-year lagged *product experience*		2-year lagged *product experience*		VC's prior 5-year experience, no lagged product experience	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VC	.054 (.038)	.055 (.038)	.115*** (.037)	.080* (.043)	.111** (.053)	.067 (.062)	.111* (.063)	.055 (.076)	.081* (.042)	.042 (.046)
VC x VC experience	.003** (.002)	.003** (.001)							.003 (.002)	.003* (.002)
VC x product experience			-.002** (.001)	-.002*** (.001)	-.002** (.001)	-.003** (.001)	-.002* (.001)	-.003** (.001)	-.002*** (.001)	-.002*** (.001)
product experience			.004*** (.001)	.004*** (.001)	.004** (.002)	.004** (.002)	.004** (.002)	.004** (.002)	.004*** (.001)	.004*** (.001)
VC x firm age				.005 (.003)		.006 (.004)		.007 (.004)		.005* (.003)
Sales	.001* (.001)	.001* (.001)	.001** (.001)	.001* (.001)	.001* (.001)	.001* (.001)	.001 (.001)	.001 (.001)	.001* (.001)	.001* (.001)
Downstream capabilities	.011 (.231)	.010 (.230)	-.174 (.246)	-.110 (.244)	-.076 (.287)	.002 (.292)	.113 (.365)	.212 (.384)	-.189 (.238)	-.122 (.234)
Innovations	.030 (.091)	.031 (.093)	.009 (.091)	-.021 (.96)	.003 (.117)	-.031 (.124)	.024 (.164)	-.023 (.173)	.008 (.089)	-.024 (.094)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	267	267	267	267	260	260	249	249	267	267
Number of observations	2325	2325	2325	2325	2058	2058	1798	1798	2325	2325
Marginal effects										
VC (average)	063* (.035)	.064* (.035)	.104*** (.036)	.067* (.041)	.101** (.050)	.054 (.060)	.100* (.059)	.042 (.073)	.079*** (.038)	.038 (.043)
VC (VC experience =low)	.054 (.037)	.055 (.038)							.072* (.040)	.031 (.045)
VC (VC experience =high)	.074** (.033)	.079** (.033)							.088** (.036)	.048 (.041)
VC (product experience =low)			.115*** (.037)	.080* (.043)	.111** (.053)	.067 (.062)	.111* (.063)	.055 (.076)	.088** (.040)	.050 (.045)
VC (product experience =high)			.086*** (.033)	.045 (.040)	.083* (.046)	.033 (.057)	.080 (.054)	.017 (.069)	.063* (.035)	.018 (.041)

Notes: 1) Heteroskedasticity robust standard errors clustered over firms are in parentheses. 2) * significant at 10%, ** significant at 5%, *** significant at 1%. 3) We define *VC experience* and *Product experience* to be low when it is at 10th percentile and high when it is at 90th percentile. 4) Although the coefficient and the robust standard error of *Sales* look like the same, it is because we round up the robust standard error to 3-digit. The robust standard error of *Sales* is mostly around .0005, and the coefficient of Sales is mostly significantly positive at 10%.

Table 4: Add interaction with VC experience and interaction with firm's product experience, OLS model, baseline sample

The other potential alternative interpretation on the estimate of this interaction is that for the firms that received VC financing, one important role of VCs is to help these firms deliver products more economically. Given the difficulty in straddling on both the old and new platform, if the VCs expect the firms to launch cloud-based products in the foreseeable future, they would guide the firms to strategically reduce the current efforts on developing the traditional C/S products. This mechanism would somewhat differ from the weaker complementary role of VCs in firms that already invested substantially in their C/S products. To probe this possibility, we lag the product experience by one year and by two year, with and without the interaction between VC and firm age. The results are reported from columns (5) to (8) in table 4, which show similar results as the ones using no lagged measure.

Next we examine a specification that includes the interactions with both VC experience and the firm's product experience. The results are presented in columns (9) and (10) in table 4. If we do not control for the interaction of VC and firm age, as shown in column (9), on average, receiving VC financing is associated with a 7.9 percentage point increase in the likelihood to launch cloud product; this effect is stronger when the VC has high level of IT-related experience, though the difference of the marginal effects between high and low level of VC experience becomes somewhat weaker with a p-value of .108. Consistent with columns (3) through (8), the role of VC in complementing a firm's decision to launch cloud seems weaker when the firm has gained substantial product experience, and the difference between high and low level of product experience is significantly different at the 1% level. In column (10), we add the interaction of VC and firm age. In this case, the economic and statistical significance of VC on a firm's cloud launch decision becomes a bit weaker, though we are still able to observe statistically significant interactions with VC experience and firm's product experience.

Conclusion

This study aims to take a first step towards examining the role of VCs in the diffusion of new technological platforms through their influences on the start-up firms' product development decisions. Focusing on cloud computing as our empirical setting, our results show a strong complementarity between VC financing and cloud offering. This complementarity is more pronounced when the VCs have richer technological experience, and is lessened if the startups already have significant experience in the old C/S technology.

Our research highlights the critical role of VCs in the development of a new technological ecosystem. In their quest of high valued financial exits, VCs ensure that capital, as well as other necessary resources, are channeled to new businesses that either offer these new unproven technological platforms or offer products that utilize them. As a consequence, enough products are developed and a vibrant ecosystem is formed to make these new platforms viable. Accordingly, from the point of view of industrial dynamics, VC investment acts as a coordination and instigation mechanism in ushering new technologies.

Our research presents several contributions to the literature. While a stream of studies have assessed different roles played by VCs in firm innovation (e.g., Hellmann and Puri 2000, Kortum and Lerner 2000), our study is the first one that focused on VCs' influence on facilitating the transition to new platforms. It also adds to a growing body of IS literature that examines the interplay between VC financing and product competition in IT industry (e.g., Kim et al. 2014). By highlighting the importance of VCs in catalyzing the transition to new platforms, our study also contributes to a stream of IS studies that investigate issues surrounding technological platforms in the IT industry (e.g., Huang et al. 2012).

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