VENTURE CAPITAL’S ROLE IN THE FORMATION OF A NEW TECHNOLOGICAL ECOSYSTEM: EVIDENCE FROM THE CLOUD

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ABSTRACT

The evolution of Information Technology (IT) platforms is an area of rapidly growing interest for information systems researchers. Of special interest has been the role of third parties such as venture capital (VC). The literature on VC argues that VCs are central agents in influencing the path and rate of IT development trajectories. However, empirical research to elaborate on these points is lacking. Using a novel approach, we examine how VC facilitates new ventures’ product development decisions to use new IT platforms. Focusing on the recent rapid rise of one such platform, cloud computing, we assembled a unique dataset to look at the period just before the cloud’s wide acceptance. Developing and testing a set of hypotheses using this dataset, we find evidence of 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 VC that had rich experience in the IT industry and are significantly weaker for firms that had prior experience developing traditional client/server products. In so doing, we provide evidence that VC does play a role in the creation of new technological ecosystems.

Keywords: cloud computing, complementarity, platform ecosystem, product introductions, venture capital
INTRODUCTION

The evolution of information technology (IT) platforms has been an area of increasing interest for information systems researchers (Tiwana, Konsynski, and Bush 2010). One classic research theme in this literature has been inquiry into the causes behind the diffusion of new platforms to users and the parallel spread of platform technologies among producers (Farrell and Klemperer 2007). In particular, when producers or users invest in new platforms they require complementary inputs that are frequently scarce during the early stages of platform diffusion. Researchers have investigated a range of institutional mechanisms that have been brought to bear to encourage the provision of these complementary inputs, including the governance of platforms by platform leaders (Gawer and Cusumano 2002; Gawer and Henderson 2007)\(^1\) and the development of standards by standard setting organizations (Augereau, Greenstein, and Rysman 2006; Rysman and Simcoe 2008).

Third-party market participants can sometimes play an important role in helping producers and users migrate to new platforms: For example, the information systems (IS) literature has frequently highlighted that IT outsourcing firms can help users migrate and adjust to new technologies and platforms (Ko, Kirsch, and King 2005). However, at present we know less about the institutions that help IT producers migrate to new platforms. In this paper, we investigate the role of one institution: venture capital.

Venture capitalists are increasingly seen as playing a critical role in influencing the rate of success, internal functions, and specific tasks in new businesses growth.\(^2\) A growing literature within IS has investigated the conditions under which start-up firms will receive venture capital.

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\(^1\) There is a growing theory literature that examines the implications of platform strategy and governance. For a recent review, see Parker and Van Alstyne (2014).

\(^2\) For a recent survey of venture capital research covering these and many other areas, see Da Rin et al. (2013).
financing (Aggarwal, Gopal, Gupta, and Singh 2012; Greenwood and Gopal 2010). However, despite the important role of VCs in facilitating the development of new industries and technologies, and the widely held belief in both academia and industry that VCs’ active involvement in all aspects of the companies that are targets of their investment is what makes them different from other private equity investments, the reality is that we have very little systematic empirical evidence on the role that VCs play in technology development at the firms in which they invest and the resulting effects on the diffusion of new platforms. This leaves a crucial gap in our understanding.

As a first step in advancing our knowledge in this key area, this paper focuses on the role of VCs in the creation of new technological ecosystems. In particular, it examines how VCs facilitate new ventures’ product development decisions to use new technological platforms. Our key argument is that VCs play important coordination and instigation roles in the rapid diffusion of new platforms. We argue that, in so doing, VCs can play a critical role in the development of a new technological ecosystem—that is, a paradigmatic shift in how core technologies are used. For such shifts to occur, it is not enough for the technology to be developed or even for a lead company to develop a product; an entire array of products and functions at a systematic level have to emerge in parallel (or at least in a sufficiently condensed period) so that companies switch to the new technology. The VC business model specifically seeks “big-ticketed” financial exits that will not only cover the losses of their other investments but also leave behind enough payout to offer high rates of return to their own investors. The main way to achieve these kinds of exits is by betting early on new platform technologies in the hope that their invested companies will become the next Oracle, Apple, or Salesforce.com. By aggressively investing in new unproven technological platforms, VCs ensure that capital is channeled to new businesses that either offer these platforms
or offer products that utilize these platforms. As a consequence, on the macro level, enough products are developed and a vibrant ecosystem is formed to make these new platforms viable.\(^3\)

We examine the salience of these arguments by developing and testing a set of hypotheses within the context of the recent rapid rise of a new computing platform, cloud computing. We focus on a particular use of cloud computing, namely, as a platform to offer Software as a Service (SaaS), which refers to software that is delivered over networks and is managed by a central provider.\(^4\) Our empirical investigation focuses on the period before the widespread acceptance of cloud computing and hence is based on a 1999-2009 sample of start-up firms that offer enterprise software products. This was one of the first crucial areas of computing to use cloud computing and includes such well-known firms as Salesforce.com; further, over this period, enterprise software firms had a clear decision to make as to whether to offer new products “over the cloud” or through a traditional client/server (C/S) platform, a key requirement of our research design.\(^5\)

We focus our attention on one key way in which VCs can facilitate the transition to a new platform, examining in particular whether VC financing is complementary to a start-up firm’s decision to offer cloud products. If complementarities exist, the value of software firms producing cloud products will be greater in the presence of VC financing and vice-versa.\(^6\) Our focus on complementarity reflects the traditional challenge in VC research: identifying whether selection or treatment effects are behind observed empirical relationships between VC financing and

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\(^3\) The logic of argument is similar to the one made by the notable economist and venture capitalist William Janeway, who specifically argued that successful financial exits based solely on the promised returns of as-yet unproven technology are necessary for what he called “the Innovation Economy” to operate. Janeway (2012) went so far as to suggest that periodic financial bubbles around new technologies are necessary for the VC model to succeed.

\(^4\) SaaS and the cloud are of course not one and the same. SaaS business models existed before the advent of cloud computing, and the cloud is, of course, much more than SaaS (see Kushida et al., 2010). For these reasons, we ensure that our sample consists only of companies that are cloud-based SaaS.

\(^5\) Our focus on enterprise software firms also allows us to contribute to an evolving literature in IS on the strategic behavior of firms in this industry (Chellappa and Saraf 2010; Huang et al. 2013).

\(^6\) For examples of research on complementarities between organizational practices, see Athey and Stern 1998; Cassiman and Veugelers 2006; Milgrom and Roberts 1990; Novak and Stern 2009.
outcomes (e.g., Sørenson 2007). In our setting, we do not seek to distinguish between sorting and treatment explanations, and 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 (e.g., Arora 1996; Novak and Stern 2009); in particular, we examine whether the likelihood of adopting the cloud is greater in the presence of VC financing. This approach reflects in part data constraints; we do not possess detailed data on the inputs and outputs of our start-ups that we would need to measure how specific combinations of practices influence firm outcomes. We find that receiving VC financing is associated with a significant increase in the likelihood of launching a cloud product. While we do not seek to explicitly distinguish between sorting and selection explanations, we investigate other ways in which omitted variables might influence our results, investigating the robustness of our results to instrumental variables estimation. In addition, we conducted a few targeted interviews of leading VCs to ensure that our interpretation of the results fits with their understanding of the VC industry’s investment dynamics.

We further probe the ways in which VC funding complements the cloud. In particular, we investigate the circumstances in which VC funding is most strongly associated with a cloud computing strategy. The results suggest that the impact of VCs on the technological decision are: (1) significantly stronger for firms backed by VCs that had rich experience in the information and communications technology (ICT) industry; and (2) are significantly weaker for firms that have prior experience developing traditional C/S products. These results are robust to alternative measures of the VCs’ experience and a variety of specifications.

Further, we examine whether VC financing is complementary to producing cloud products because of the unique cash flow needs associated with them. Because of their use of a services
rather than licensing revenue model, cloud firms may initially have slower revenue growth per
customer than similar C/S firms and may have higher costs if they are forced to develop products
for two separate platforms. This suggests that cloud firms may have greater funding needs. We
find evidence consistent with this hypothesis, showing that delivering cloud products is associated
with more intensive financing and that this finding is particularly strong when cloud and C/S
products are produced together.

Our research offers several contributions to the literature. First, our research furthers
understanding of how IT producing firms transition to a new platform. Decisions to deploy
software over the cloud involve both a set of technological investments required to adapt new
general-purpose IT to specific requirements and a set of organizational and business model
changes for start-ups. The challenges in this type of complementary innovation are well known
(e.g., Bresnahan and Greenstein 1996; David 1990; King et al. 1994). Much of the research in this
literature has focused on the technological transitions of large firms (Bresnahan and Greenstein
1996; Bresnahan et al. 2002; Rothaermel and Hill, 2005). Further, while they explicitly
acknowledge and argue for the role of third-party intermediaries, such as outsourcing firms that
facilitate these transitions, it has historically been difficult to observe the implications of such
intermediaries for firm outcomes. Shifts to new technological platforms often give rise to
significant change in business models. In particular, the increasing digitization of economic
activity has inspired a range of new business models that heretofore would not have been feasible.\(^7\)

While researchers have begun to analyze potential business models for cloud computing and
software as a service in particular (e.g., Cusumano 2010a, 2010b; Cusumano et al. forthcoming),

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\(^7\) The number of recent papers in this area are far too numerous to cover here. For some recent examples, see Gans (2012) and the
papers in Goldfarb et al. (2015).
our research contributes to this evolving literature using new data and highlighting VCs as an important third-party intermediary to address challenges in making such transitions.

Further, our main hypothesis that VCs facilitate the transition to new technology platforms is motivated by prior research on the investment behavior of VCs and the value-adding services that they provide. In particular, we build upon prior findings that VCs play an important sorting role in identifying firms pursuing innovator strategies (e.g., Hellmann and Puri 2000); that provide access to private information for their invested firms (e.g., Hsu 2006); and that VCs play a role in building the internal organization of their portfolio firms (e.g., Hellman and Puri 2002). However, none of these papers explore the primary hypothesis of this paper: that VCs play a role in determining the technological trajectory of their invested firms, specifically in helping their portfolio companies’ transition to a new technology platform.

THEORETICAL MOTIVATION

Challenges in Developing Products on New Technological Platforms

For a new technological ecosystem to emerge, a range of products and functions at a systematic level have to be developed in parallel for companies to switch to the new technology. For example, it was not enough for the personal computer to be invented and for significant competition to develop between various makers of personal computers (PC). Only after an entire ecosystem of software, services, data communication, and skills evolved around the specific Windows-Intel (also known as Wintel) platform did companies shift their computing paradigm away from mainframe, mini, and workstation computing and toward the PC and its client-server architecture.

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8 The “prominence” of the IBM PC is now so etched into our public mythology that it is little known 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.

9 For a case study of how the computer software industry fared during this transition, see Campbell-Kelly (2003).
The lack of such an ecosystem is believed to be one reason for the slow diffusion of the client-server architecture within businesses early on (Bresnahan and Greenstein 1996).

Although it is tempting for start-up firms to develop new products using an emerging technological platform, they may face several challenges that prevent them from doing so. The first challenge in forming a new technological ecosystem is coordinated instigation. Enough actors (i.e., VCs) need to be reassured that other actors are working on other necessary aspects of the technological-business problem so that when they come up with their specific solution it will be viable on both the technological and the business front. Otherwise, it would be irrational for those VCs to invest.

In some fields, public or public-private solutions to the coordinated instigation problem exist. A widely cited example of such solutions is the International Technology Roadmap for Semiconductors, which ensured widespread agreement on goals, standards, and time frames and stimulated investment from a wide range of actors around the globe to achieve its stated goals of technological development (Brown and Linden 2009). Large firms can sometimes play a similar role, as their importance allows them to set standards and manage the transition to new platforms; for example, Intel has entered complementary markets with the explicit purpose of generating new markets and expanding existing markets for its microprocessors (Gawer and Henderson 2007). Focal products can sometimes play a similar role in coordinating behavior; for example, the initial diffusion of the browser in the 1990s is widely believed to have helped market participants understand how the Internet could be used as a platform to coordinate economic activity (Cusumano and Yoffie 1998; Greenstein 2010). However, these types of institutions and coordinating mechanisms do not always exist.
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 from which to learn. For example, given the lack of mature markets for many types of software, early adopters of C/S computing were forced to undertake a variety of development work and complementary innovation to adapt new C/S infrastructure to idiosyncratic firm needs (Bresnahan and Greenstein 1996). Firms with better technical teams will have an advantage in identifying difficulties and taking the lead on the new technological trajectory.

Yet even a start-up with the best quality human capital can 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 in which core technologies are used may be completely different from those on the old platform, the start-up firms need to develop new technical components or change old designs completely. Second, commercializing the new product 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 had to identify new business models and sort out licensing and legal issues but also had to expend tremendous energy in reorganizing 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 great deal to promote the new technology on the market. For instance, to promote its on-demand customer relationship management (CRM) product, Salesforce.com spends roughly 50% of its yearly revenues on marketing, so it has a thin profit margin.
Further, the above discussions are not a comprehensive list of challenges that the start-up firms could face when developing new products on an unproven technological platform. They are just some common problems. Interestingly, many of these problems can be addressed by VCs. Our next section therefore discusses the role of VCs in addressing these challenges.

**The Role of VCs in Complementing a Firm’s Product Development on New Technological Platforms**

VC firms (or funds) are usually organized as partnerships between general partners (GPs) and limited partners (LPs). GPs are a few individuals who make the investment choices, assert active management, and are involved in the companies in which the fund invests. LPs are a set of institutional 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 as a venture capitalist.

The literature has suggested that VCs play several roles in facilitating the evolution of a new ecosystem. First, VCs are able to screen and identify better-quality ideas and firms in which to invest. Regarding their role in picking firms with the best innovations, Hellmann and Puri (2000) show that companies that follow innovation strategies are more likely to get VC funding than those that pursue imitation. Similarly, Chemmanur et al. (2011) provide evidence that the productivity of VC-backed firms is higher before receiving VC funds than that of non-VC-backed firms.\(^\text{10}\) The idea that VCs are better in screening and identifying better quality ideas was echoed when we interviewed a prominent Silicon Valley VC, who stated that:

“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 consultants to be able to know of new technological trends as soon as they appear. We find this very worthwhile, leading, over the years, to some of our best ‘hits’.”

\(^{10}\) For more examples, see the review in Da Rin et al. (2013).
VC funds may also have a specific focal area of interest, as in a new technological area such as cloud computing, and so may play a similar role in screening companies that may fit particularly well with the goals of the fund. Similarly, some interviewees told us that some funds have specific initiatives aimed at specific technologies. Sometimes, these are posted directly on a VC’s website; for example, in 2010 Kleiner Perkins Caufield Byers launched a $250 million fund aimed directly at the social web (KPCB 2010).

Therefore, we argue that because VCs tend to develop various techniques for keeping 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, pushing them into the new technologies, and betting on them early. Further, such strategies maximize the VCs’ potential profits. The impact of such behavior at a systematic level is that 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 consumers.

The second important role of VCs that has been emphasized in the literature is that of being information intermediaries for their invested firms (Hsu 2006). 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 might also be more aware of 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 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. In addition to monitoring the invested firms (Florida and Kenney 1988; Gompers and Lerner 1999; Lerner 1995), VCs also play an important role in building the internal organization, formulating human resource policies, and hiring the vice-president of sales and marketing (Hellmann and Puri 2002). We argue that 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 a new platform.

VCs may also be able to help start-ups producing for a new platform with their unique financing needs. Because of limited experience with the new technology, external funding sources may have a difficult time evaluating the risk of investing in a new platform. VCs, because of their active role on the boards of companies, may be better able to evaluate the risks and potential returns of such investments (Dushnitsky 2010; Puri and Zarutski 2012; Winton and Yerramilli 2008).

All the foregoing discussions suggest the significant role of VCs in addressing the challenges of developing products on an unproven platform. It is not our goal to empirically disentangle the mechanisms through which VCs ameliorate these challenges. Rather, together they support our argument that because VCs increase the net benefits from developing new products on an emerging platform, all else being equal, we would expect to observe complementarity between VC financing and launching products on a new technological platform.

Both theory and some findings (Bottazzi et al. 2008; Gompers et al. 2009) suggest that the more experienced the VCs are as technologists and entrepreneurs, the better they are at performing the functions described above, including selecting the best ideas and firms, mitigating costs
involved with new product development, and providing active management guidance. As a result, we expect that the complementarity between VC financing and launching a product on a new platform will be stronger when VCs have gained 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 weaker complementarity. This might occur for several reasons. First, to the extent that such firms may already have significant sunk costs from developing products for the old platform, they may reap lower net benefits from 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 using the old platform. It may have also developed an understanding of business models that work on the old platform. If these capabilities are not well suited 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 them 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 this hypothesized influence of VCs, we look at the early stages of a new paradigmatic technological shift (that is, the period before the technological acceptance takes off). Those shifts happen during the early stages of diffusion of a new paradigm of computing that revolutionizes the ways in which information systems are used, before the emergence of an ecosystem of complementary institutions and services. As we describe in further detail below, the
early stages of cloud computing, *before it became clear that the new paradigm was taking hold*, supplies a rich case study for examining how VCs influenced firm decisions on developing products based on the new, yet-to-be-proven paradigm. Based on our discussions above, we posit the following three testable hypotheses in the context of the period “ahead of the technology acceptance curve”:

**Hypothesis 1:** VC financing is associated with an increase in the likelihood of a new computing paradigm product launch by a start-up firm

**Hypothesis 2:** VC financing is associated with a greater increase in the likelihood of a new computing paradigm product launch when the VC has rich experience in the IT industry.

**Hypothesis 3:** VC financing is associated with a smaller increase in the likelihood of an initial new computing paradigm product launch when the start-up firm already has rich product experience using existing computing technologies.

**Institutional Setting: Cloud Computing**

There remains significant confusion about what constitutes cloud computing and what, if anything, is new in cloud computing compared to prior computing platforms. We define cloud computing following the definition of Kushida, Breznitz, and Zysman (2010, p. 2): “Cloud Computing provides on-demand network access to a computing environment and computing resources delivered as services. There is elasticity in the resource provision for users, which is allocated dynamically within providers’ datacenters. Payment schemes are typically pay-as-you-go models.”\(^{11}\) Importantly for our purposes, cloud computing defines both a technical architecture and a business model. The computing resources that are delivered as services can be applications, platforms, or infrastructure. In this paper, because we focus on enterprise software, we concentrate

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\(^{11}\) This definition draws upon one created by the U.S. National Institute of Standards and Technology (NIST) (Mell and Grance 2011), as well as Armbrust et al. (2009) and Murray (2010).
on software applications that are delivered as services (Software as a Service). Again using the definition of Kushida, Breznitz, and Zysman (2010), “Software as a Service (SaaS) refers to software that is delivered or accessed over networks. Software is managed centrally by the SaaS provider, relieving the IT managers of users from dealing with incremental upgrades and security patches to end-user PCs.”

Enterprise software consolidates the information needs of a firm’s departments into a single, integrated software program that operates on a shared database. Enterprise software is used to run the back office operations of a firm and includes enterprise resource planning (ERP) and customer relationship management (CRM) software as well as other applications. We focus on enterprise software to reduce the extent of unobserved heterogeneity in our sample, which will be important as the incidence of VC funding and the cloud business model may both be influenced by unobserved factors, as we address in further detail below. 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 applications created specifically to offer services via the Internet—such as some Google applications—because many enterprise software firms are operating on client data, they faced a clear choice of business models.12

Producers of enterprise software during our period had a choice of offering C/S software or SaaS. C/S software is delivered as a product to the customer’s premises to reside within the customer’s IT infrastructure. Using this option, customers usually purchase a perpetual software license upfront, with maintenance fees and the potential for periodic upgrades (usually associated with a new license fee). Because it is offered as a product and deployed on the client’s system, the client also has the opportunity to customize the software. In contrast, using the SaaS model, the

12 For examples, see Burgelman and Manoharan (2009); Burgelman and Schifrin (2014); and Coates et al. (2008).
software is hosted by the provider and delivered over the Internet using a standard web browser. In contrast to C/S software, for which payment is an upfront capital expense, SaaS is a pay-as-you-go model in which the client leases use of the software service. Although initial customization is limited under SaaS, the existence of only one primary instance for the software makes it easier for the firm to update it regularly (e.g., every six weeks or even more frequent).

The differences in business model may create unique challenges for cloud firms compared to those offering products for a C/S infrastructure. First, the cash flow pattern is significantly different for the two business models: while the cash flow from new customers is front-loaded as they pay for new perpetual licenses, the cash flow to the provider of new SaaS licenses is spread out over time. Thus, although a new SaaS product could generate significant growth in new customers, growth in realized revenues and cash flow from those customers comes more slowly (Burgelman and Manoharan 2009; Burgelman and Schifrin 2014; Coates et al. 2008). More broadly, companies offering cloud products were forced to experiment with new revenue models—such as deciding whether to price by the number of users or by application usage (Burgelman and Manoharan 2009)—for which at first there was relatively little data to inform behavior. The issues of new cash flow patterns, combined with additional expenses (described below), has the potential to create cash flow problems for cloud providers.

Software developed for the cloud differs in many respects from that developed for a C/S application. First, delivering software services favored an approach to developing reusable software components rather than a single monolithic application (Coates et al. 2008). Such an outlook may require different application developers (who may be in shorter supply) and a different structure for the development group than is the case under traditional C/S (e.g., Moore 2006). Second, as noted earlier, a cloud environment offers the opportunity for more frequent
product releases (e.g., Coates et al. 2008). Third, customers for C/S and cloud software are likely to differ significantly: Customers for C/S are likely to be large enterprises that prefer full-featured software, which they may be able to customize; in contrast, clients for cloud software, on average, are smaller and may be satisfied with less flexibility and potential for customization. These differing requirements can increase the costs and put strains on the cash flow for firms that have developed C/S software but are entering the market for cloud software.

Because the cloud represented a new delivery platform, vendors seeking to deliver software services in this way had to design new models of customer engagement. Traditional on-premises C/S software often involved sales through account executives who played an active, consultative role with customers, seeking to show how the system could best be employed to meet the client’s needs. This type of high-touch sales often meant significant sales delivery costs and high commissions, which were justified given the potentially high revenues associated with sales to on-premises customers. In contrast, because revenues for a SaaS sale were significantly lower and involved less consultation, the role for sales forces was different and necessarily required a different compensation structure (Petty 2008). The diffusion of cloud computing meant that new models for developing, training, and compensating sales forces needed to be developed. Where a sales force for C/S already existed, a natural tension existed between compensation, training, and incentives across the two channels that was often only unwound over time (e.g., Coats et al. 2008).

**EMPIRICAL FRAMEWORK**

In the specific empirical case of cloud computing, we argue that VC financing is complementary to the introduction of new products offered over the cloud—that is, the returns to offering cloud products will be greater in the presence of VC financing and vice-versa (e.g., Brynjolfsson and Milgrom 2013). Two classes of statistical tests have been used to detect complementarities: (1)
correlations in the adoption of practices; and (2) evidence of systematic performance differences, such as productivity (Brynjolfsson and Milgrom 2013). Because we have limited information on inputs and outputs of the start-ups in our data, we are unable to study the performance implications of VC financing and the decision to offer cloud products and, instead, study correlations in the decisions to adopt VC and cloud delivery.\textsuperscript{13}

Specifically, our empirical approach most closely follows that of Novak and Stern (2009). Suppose there is an observable binary status on whether a firm launches its initial cloud product, denoted as $k = \text{Initial cloud product launch}$, with net benefits to the firm denoted by $\beta_k$. Both the firm $i$ and the econometrician observe a vector of decision-specific drivers $Z_{ki}$ with marginal returns to the firm as $\delta_k$. There are also some decision-specific mean-zero shocks $\eta_{ki}$, which are observed by the firm but not the econometrician, and can be composed into $\xi_i$ (i.e., firm-level shock for firm $i$) and $\epsilon_{ki}$ (i.e., some shock related in particular to firm $i$’s cloud product launch decision).

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

$\text{Initial cloud product launch}_i = 1$ if $\lambda_{VCi} + \beta_k + \delta_k Z_{ki} + \xi_i + \epsilon_{ki} > 0$, where $k = \text{Initial cloud product launch}$. \hfill (1)

In equation (1), $\lambda$ captures the benefits from VC (an observable binary status on whether the firm has successfully attracted VC financing) to the marginal returns to a cloud product launch.

\textsuperscript{13} Researchers who have studied the implications of VC funding have sometimes focused on alternative outcome measures, such as whether the start-up has an IPO (e.g., Hsu 2006; Shane and Stuart 2002). However, the number of IPOs we observe in our sample is small (10), making inferences difficult. This small number reflects both the relatively small size and the recent nature of our sample period; the incidence of IPOs is likely to be right-censored in our data.
Our main objective of the empirical analysis is determining whether $\lambda$ is greater than zero. If we convert equation (1) to a linear probability model, it can be written as follows:

$\text{Initial cloud product launch}_i = \lambda V C_i + \delta_k Z_{ki} + \eta_{ki}$, where $k = \text{Initial cloud product launch}$.  \hspace{1cm} (2)

Because the firm-level shock $\xi_i$ is included in $\eta_{ki}$, a cross-sectional estimation using ordinary least squares (OLS) will lead to a biased estimate of $\lambda$, because $\xi_i$ might be also correlated with VC financing (i.e., $V C_i$). For example, a positive $\lambda$ may not be caused by the complementarity between the two; instead, it might occur if a firm with an excellent team of internal directors tends to attract VC financing as well as launching a 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 a 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:

$\text{Initial cloud product launch}_{it} = \lambda V C_{it} + \delta Z_{it} + \mu_i + \tau_t + \eta_{it}$ \hspace{1cm} (3)

$\text{Initial cloud product launch}_{it}$ is a binary variable that equals 1 if firm $i$ launches its first cloud product in year $t$ and equals 0 otherwise; $V C_{it}$ is also a binary variable, which equals 1 if firm $i$ has received VC by year $t$ and 0 otherwise. The parameter $\lambda$ captures the complementarity, and our interest is in testing whether $\lambda > 0$. $Z_{it}$ is a set of control variables that vary by firm and by year and could potentially influence the firm’s decision to launch a cloud product. $\mu_i$ represents the time-invariant unobserved firm heterogeneity, and $\tau_t$ 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 a cloud product.
Nevertheless, one could still argue that some time-varying components in $\eta_t$, 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, in particular, the SaaS model. The sample firms come from the 2003, 2004, and 2010 editions of the CorpTech Directory of Technology Firms (hereafter, CorpTech) with the primary SIC code 7372. \(^\text{14}\) Our sample years range from 1999 (the last year in which the concept of cloud computing had not yet formed) to 2009 (by which time 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 up-and-coming computing platform).

Although our CorpTech data have detailed information on the product market segments of firms, they do not vary over time from 2005 to 2009. Therefore, we combine the data extracted from CorpTech with 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 only on start-up firms, we restrict the sample to firms that were founded after 1990 and that have fewer than 1,000 employees and less than $500 million in annual sales, which gives us a total of 339 firms.

\(^\text{14}\) 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.
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 a firm’s first introduction of cloud products, we first 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). Second, 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 the cloud in the SaaS category, as our sample firms produce primarily 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 articles on new product introductions. Fourth, we manually read all search results to eliminate false positives by ensuring that we had correctly identified cloud product introductions. In all, 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 the initial cloud product launch—that is, the first time a firm releases a product over the cloud. Therefore, we dropped all observations for a firm after it introduced its first cloud product, as the firm is no longer exposed to the hazard of offering an

---

15 The exact phrases we used for text search include the following: cloud, software-as-a-service, SaaS, Internet-based, Internet-enabled, web-based, web-enabled, Internet delivery, web delivery, on-demand, subscription-basis, subscription-based, usage-basis, usage-based, pay-as-you-go, pay-as, pay-per, pay-for-use, pay-for. For those with hyphens, we also searched for the phrases without them.
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 omit these 72 firms from our baseline sample. However, as discussed below, we test the robustness of our results using the full sample. In summary, our baseline sample consists of an unbalanced panel with 2,325 observations by 267 firms from 1999 to 2009. Among the 267 firms, 42 firms (15.73%) eventually released a cloud product by the end of our sample. Table 1 lists summary statistics for the main variables used in the empirical analysis over our entire sample period.

**Independent Variables**

**VC.** This variable indicates whether a firm 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 in which VCs invest, including the date of 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 that 73 firms (27.34%) in our baseline sample had received VC funding by the year they launched the first cloud product. Following the literature (e.g., Hsu 2006), we consider receiving VC an absorbing state. Therefore, if a firm $i$ received the first round of VC funding in year $t$, the variable $VC$ equals 1 in year $t$ and all following years, and otherwise it will equal 0.

---

16 One firm in our sample received VC after its first cloud. Because our baseline sample drops observations after the first cloud, this firm is not considered a VC-funded firm in the baseline analysis. However, in section 5.4, where we focus on the set of VC-funded firms during the entire sample period (from 1999 to 2009), this firm is incorporated into the analysis.
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 five-year experience (denoted as VC’s prior five-year experience) as the baseline measure, as we believe that using the prior five-year window reflects the 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 the 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 of funding the lead VC. Second, we extracted all VC funding activities in portfolio companies operating in the 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 five-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 for each VC-backed sample firm, we know its lead VC’s experience in the IT industry as an early-stage investor. For firms backed by multiple lead VCs, we use the average experience.\(^{17}\)

C/S 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

\(^{17}\) 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 are available upon request.
employed a combination of automatic search and manual reading to identify the sample firms’ product introduction events. 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 the cloud as described above. Because we do not have data on 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 \( t \).

**Control Variables**

*Trademarks.* As has been suggested by Fosfuri et al. (2008), when a firm invests 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 are also likely to correlate with the opportunity for VC funding. To control for this effect, following prior literature (Huang et al. 2013), we extract trademark data from the U.S. Patent and Trademark Office (USPTO) and use the count of live trademarks (in thousands) held by firm \( i \) up to year \( t \).

*Patents.* Prior literature highlights that VCs tend to fund firms with demonstrated innovation capabilities (Conti et al. 2013; Mann and Sager 2007). A highly innovative firm will also be more likely to follow new technology paradigms. In line with the existing literature that studies the relation of VC to firm innovation output (Kortum and Lerner 2000), we use patents as a measure of a 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 National Bureau of Economic Research (NBER) Patent Data Project and the USPTO website. We use claims-weighted counts (in thousands) 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 a patent. We further use
the raw count of granted patents, the claims-weighted count of patent applications, and the raw count of patent applications for firm $i$ up to year $t$ as a 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 millions) data during the 1999-2009 period from the NETS Database (denoted as sales). We also demonstrate the robustness of our results to using the number of employees as an alternate measure of size.\(^\text{18}\) As has been discussed elsewhere, firm age is also an important factor that affects both a firm’s financing opportunity and its 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 other models that do not use firm fixed effects.

<table>
<thead>
<tr>
<th>Table 1: Summary Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable names</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>VC</td>
</tr>
<tr>
<td>VC’s prior five-year experience</td>
</tr>
<tr>
<td>Initial cloud product launch</td>
</tr>
<tr>
<td>Sales</td>
</tr>
<tr>
<td>Trademarks</td>
</tr>
<tr>
<td>Patents</td>
</tr>
<tr>
<td>Age</td>
</tr>
</tbody>
</table>

\(^{18}\) We did not use both sales and employment as controls for firm size, as these two variables are highly correlated.
Notes: 1) The baseline sample includes 2,325 observations by 267 firms; the sample of firms funded by VC includes 583 observations by 73 firms; the sample of firms not funded by VC includes 1,742 observations by 194 firms. 2) ** significant at 5%, *** significant at 1%.

**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 framework. Second, we test the robustness of the results using a different sampling strategy and an alternative empirical model. We further try to examine how omitted variable bias might affect our results through instrumental variable estimation. Third we demonstrate how influence by a VC is shaped by its past experience in the IT industry and the start-up firm’s existing C/S product experience. Fourth we examine the unique role that VCs play in helping start-ups overcome financing constraints when they invest in new technological platforms.

**Baseline Results and Robustness Tests**

Figure 1 presents a time-series chart of the cumulative percentage of the sample firms that launched cloud products for the first time, for VC-backed versus non–VC-backed firms. Overall, while firms rarely entered into the 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-backed firms.
In Table 1 we examine the differences in our summary statistics for firms that are and are not backed by VCs and conduct a nonparametric test of variable differences between the two subsamples. As shown in Table 1, firms that received VC are more likely to launch cloud products; they also have greater experience with traditional C/S products (as proxied by the cumulative number of C/S products introduced since 1999), are associated with a higher number of claims-weighted patents, are younger, and have fewer trademarks. However, they do not exhibit a significant difference in sales compared to the VC-funded firms.

The comparisons between the two subsamples in Table 1 reveal significant differences in firm characteristics between firms that received VC financing and those that did not. One particular concern is that some unobserved differences related to those firm characteristics may correlate with both the chance of receiving VC financing and the decision to offer cloud products. Therefore, as discussed in Section 3, we use a fixed-effect linear probability model, that is, equation (3), as our baseline specification. We include sales, trademarks, and patents in all regressions as baseline time-varying controls, as we think these factors may affect a firm’s likelihood of receiving VC funding as well as its likelihood of launching a cloud product. While C/S product experience may also have a significant effect on a cloud launch, this variable itself may be correlated with unobserved firm quality that affects VC funding opportunity and the cloud launch decision.
Therefore, \emph{C/S product experience} is excluded from the baseline controls, but we include it in some specifications as a robustness check.

Table 2 below focuses on exploring the basic relationship between VC and a firm’s cloud launch decision. Column (1) in Table 2 reports the results with the baseline controls, and column (2) includes \emph{C/S product experience} as an additional control. The results are consistent across the two specifications, suggesting that receiving VC financing is associated with an increase in the likelihood of launching cloud product of 9.1 percentage points.

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. In short, our results support Hypothesis 1.

We choose a 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. More specifically, we choose the Cox proportional hazard model, as it is a semiparametric model that makes no assumption about the shape of the baseline hazard over time and assumes that covariates are multiplicatively related to the hazard. In our setting, suppose that \( h_i(t |X_{it}) = h_0(t) \exp(X_{it}' \beta) \), where \( h_i(t |X_{it}) \) is the conditional instantaneous hazard rate for firm \( i \) in year \( t \) to launch cloud products. \( h_0(t) \) is the unspecified baseline hazard in year \( t \), and \( X_{it}' \beta = \beta_1 VC_{it} + \gamma_1 Sales_{it} + \gamma_2 Trademarks_{it} + \gamma_3 Patents_{it} + \gamma_4 C/S Product Experience_{it} + \gamma_5 Age_{it} + \tau_i \).
The results based on the Cox proportional hazard model are presented in columns (5) and (6) in Table 2. The marginal effects are represented in semi-elasticities and suggest that after a firm receives VC funding (i.e., the variable \( VC \) has a discrete change from 0 to 1), the firm exhibits an increase of 138%-144% in the hazard rate of launching cloud product.

### Table 2: Direct effect of VC on initial cloud product launch

<table>
<thead>
<tr>
<th>Dependent variable: Initial cloud product launch</th>
<th>Baseline sample, OLS</th>
<th>Full sample, OLS</th>
<th>Baseline sample, Cox proportional hazard models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>VC</td>
<td>.091***</td>
<td>.086**</td>
<td>.090***</td>
</tr>
<tr>
<td></td>
<td>(.034)</td>
<td>(.034)</td>
<td>(.034)</td>
</tr>
<tr>
<td>Sales</td>
<td>.001*</td>
<td>.001*</td>
<td>.001</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
</tr>
<tr>
<td>Trademarks</td>
<td>.034</td>
<td>-1.54</td>
<td>.024</td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td>(.241)</td>
<td>(.248)</td>
</tr>
<tr>
<td>Patents</td>
<td>.029</td>
<td>-.005</td>
<td>-.010</td>
</tr>
<tr>
<td></td>
<td>(.093)</td>
<td>(.097)</td>
<td>(.010)</td>
</tr>
<tr>
<td>C/S product experience</td>
<td>.003**</td>
<td>.002**</td>
<td>.007</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.009)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of firms</td>
<td>267</td>
<td>267</td>
<td>339</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2,325</td>
<td>2,325</td>
<td>3,004</td>
</tr>
</tbody>
</table>

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

### 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 products 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 a new product development strategy. We focus on the variables related to the local supply of VC funds in an area, under the assumption that VCs are more likely to fund firms in close geographic proximity. Following
Chemmanur et al. (2011), our first variable is the number of limited partners that invested in VC funds that existed over the prior five-year rolling window and are located in the same state as the sample company. The number of limited partners 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 do not 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 it is that the local VCs will raise funds and therefore the greater chance that firms will 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 in particular may show home bias. Therefore, our second variable is the number of public pension funds that invested in VC funds over the prior five-year rolling window and were located in the same state as the sample company.

Our third variable is the total number of mergers and acquisitions (M&As) in all non-IT industries in the prior two years and in the same state.\(^{19}\) The logic of using this variable is as follows. First, given the usual VC cycle, there is a significant correlation between the M&As in the previous cycle and the supply of VC funding for new ventures in the next cycle.\(^{20}\) Therefore, the more M&As in prior years, the more likely it is that our sample firms will receive VC in the current period. We measure the prior two years of M&As, as this interval can effectively predict future investments (Kolev 2013). Meanwhile, because M&As are usually driven by overall

\(^{19}\) Unfortunately, most of M&As in our dataset have missing transaction values, so we are able to compute only the number of M&As instead of the dollar value of M&As.

\(^{20}\) 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.
financial market conditions, they should be less likely to directly influence a firm’s product development strategy. To further rule out any possible correlation between M&As and our dependent variable, we focus on the M&As achieved in non-IT industries. The focus on M&As in the same state is in the same spirit as the first instrument above, that is, the home bias exhibited by the supply of VC funds.

Last, we use a dummy measure for these three variables (i.e., it equals 1 if it is above 50th percentile and 0 otherwise), to incorporate nonlinearities of their effects on VC funding. Further, because we observe very little variation in these variables over time, we interact each of them with a linear time trend (denoted as High limited partners X time trend, High public pension funds X time trend, and High M&As X time trend).

Following prior literature (Angrist and Pischke 2009), our second step is to employ a probit model to predict the likelihood that a firm will receive 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 chances of getting VC funding, though we do not find a similar effect in public pension funds.

The next step is use the predicted likelihood of receiving VC funding from this probit model in column (1) as the instrument. Because none of the above three factors should 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 based on the above three factors is strongly correlated with a firm’s true VC funding status. The $F$-statistic is 17.39, above the commonly used threshold of 10 and above the Stock-Yogo (2005) critical threshold for weak instruments. The results from the second stage show that the sign of the coefficient of VC is consistent with the baseline result, though the magnitude and standard error are somewhat higher.

<table>
<thead>
<tr>
<th>Table 3: Direct effect of VC on initial cloud product launch, instrumental variable estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>------------------------------</td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>High limited partners X time trend</td>
</tr>
<tr>
<td>High public pension funds X time trend</td>
</tr>
<tr>
<td>High M&amp;As X time trend</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
</tr>
<tr>
<td>Firm fixed effect</td>
</tr>
</tbody>
</table>

$F$-statistic 17.39 --

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%.

**Examining When the Complementarity is Stronger or Weaker**

We have tested for the presence of complementarity between VC funding and the decision to launch products on the cloud. In this section, we investigate the circumstances in which such complementarity is likely to be stronger or weaker. We first investigate H2. 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, which uses specification with baseline controls, the estimated marginal effects suggest that firms backed by VCs with little experience in the IT industry (i.e., VC experience at the 10th percentile and equal to 0) are associated with an increase in the likelihood of launching a cloud product of 5.44 percentage points, and this effect is statistically insignificant.
However, the effects of VC funding are stronger for VC with rich experience in the IT industry: firms backed by VCs that have VC experience equal to 6 (at the 90th percentile) are associated with a statistically significant increase of 7.42 percentage points (equal to \((5.44 + 0.33) \times 6\)) in the likelihood of launching a cloud product. The results are again robust if we add C/S experience as a control, as presented in column (2). We further examine the robustness of the results by measuring VC experience using prior 10-year experience, and the results are very consistent, as shown in columns (3) and (4) in Table 4. These results provide evidence of the important role of VC experience on its influence on the product development trajectory of their invested companies, and support Hypothesis 2.

We next explore how a firm’s existing C/S product experience shapes the complementarity between VC and a firm’s product development decision. We add the interaction between VC and a firm’s C/S product experience to our baseline model. As reported in column (5) in Table 4, receiving VC funding is associated with an increase of 11.5 percentage points in the likelihood that firms with C/S product experience will launch clouds products, at the 10th percentile, but is associated with an increase of only 8.6 percentage points for firms with C/S product experience, at the 90th percentile. The coefficient on the interaction term suggests a statistically significant difference between low and high C/S product experience. These results support Hypothesis 3.

However, if a start-up has low C/S product experience, it also implies that it is younger, so one explanation on the stronger effect of VC on a firm with little C/S product experience is that this type of firm is likely to be younger and thus requires greater intervention by VC. To disentangle this age effect from the product experience effect, we add the interaction between firm age and VC (denoted as \(VC \times firm\ age\)) to the regression model. The results are reported in column (6) in Table 4. The coefficient on \(VC \times C/S\ product\ experience\) remains significantly negative.
Table 4: Add interaction with VC experience and interaction with firm’s C/S product experience, OLS model, baseline sample

<table>
<thead>
<tr>
<th>Dependent variable: Initial cloud product launch</th>
<th>Interaction with VC’s prior five-year experience</th>
<th>Interaction with VC’s prior 10-year experience</th>
<th>Interaction with product experience</th>
<th>Add both interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC</td>
<td>(.038)</td>
<td>(.038)</td>
<td>(.37)</td>
<td>(.046)</td>
</tr>
<tr>
<td>VC x VC experience</td>
<td>(.02)</td>
<td>(.01)</td>
<td>(.01)</td>
<td>(.01)</td>
</tr>
<tr>
<td>VC x C/S product experience</td>
<td>-0.02**</td>
<td>-0.02**</td>
<td>-0.02***</td>
<td>-0.02***</td>
</tr>
<tr>
<td>C/S product experience</td>
<td>.003**</td>
<td>.003**</td>
<td>.004***</td>
<td>.004***</td>
</tr>
<tr>
<td>VC x firm age</td>
<td>.001*</td>
<td>.001*</td>
<td>.001*</td>
<td>.001*</td>
</tr>
<tr>
<td>Sales</td>
<td>.001*</td>
<td>.001*</td>
<td>.001*</td>
<td>.001*</td>
</tr>
<tr>
<td>Trademarks</td>
<td>.011</td>
<td>.017</td>
<td>.017</td>
<td>.017</td>
</tr>
<tr>
<td>Patents</td>
<td>.030</td>
<td>.005</td>
<td>.004</td>
<td>.004</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of firms</td>
<td>267</td>
<td>267</td>
<td>267</td>
<td>267</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2325</td>
<td>2325</td>
<td>2325</td>
<td>2325</td>
</tr>
<tr>
<td>Marginal effects</td>
<td>.063*</td>
<td>.059</td>
<td>.064*</td>
<td>.079**</td>
</tr>
<tr>
<td>VC (average)</td>
<td>(.035)</td>
<td>(.036)</td>
<td>(.036)</td>
<td>(.043)</td>
</tr>
<tr>
<td>VC (VC experience = low)</td>
<td>.054</td>
<td>.050</td>
<td>.050</td>
<td>.072**</td>
</tr>
<tr>
<td>VC (VC experience = high)</td>
<td>.074**</td>
<td>.070*</td>
<td>.079**</td>
<td>.086**</td>
</tr>
<tr>
<td>VC (C/S product experience = low)</td>
<td>.115**</td>
<td>.080*</td>
<td>.086**</td>
<td>.050</td>
</tr>
<tr>
<td>VC (C/S product experience = high)</td>
<td>.086**</td>
<td>.045</td>
<td>.063*</td>
<td>.018</td>
</tr>
</tbody>
</table>

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 C/S product experience as low when it is at the 10th percentile and high when it is at the 90th percentile.

Next we examine a specification that includes the interactions with both VC experience and the firm’s C/S product experience. The results are presented in columns (7) and (8) in Table 4. The results are qualitatively similar to those in the other columns where the effects of VC experience and C/S product experience are entered separately, however, the statistical significance of the interaction term of VC funding and VC experience is somewhat weaker.

Exploring the Interaction between VCs and Start-ups during the Post-investment Stage

As emphasized earlier, one important role that VCs play in helping start-ups transition to a new platform is providing necessary financial support. This role may be especially crucial for start-ups
that offer cloud products. In contrast to C/S firms that receive licensing revenues upfront when new products are sold, cloud firms that deliver services will receive revenue only over time because of pay-as-you-go customer relationships. This both reduces realized revenue in the early years of a start-up’s life but also increases uncertainty about the total revenue stream from any single customer. Motivated by these observations, in this section we seek to explore the financing role played by VCs in greater detail. The nature of analyses in this section of the paper is different from that in the other sections. Rather than examining the complementarity between VC funding and cloud products, in this section we examine the intensity with which start-ups receive financing, among those already receiving VC funding. That is, we explore whether VC-funded cloud start-ups receive funding in larger amounts and more rapidly than VC-funded start-ups that offer their products using other business models.

The purpose of this section is to explore in further detail how VCs help start-ups overcome the challenges associated with producing for a new platform. However, these results should be interpreted with care. In an ideal world, we would observe the rate of cash flow burn for firms that transition to producing cloud products and compare that to the cash flow of firms that do not offer cloud products, among the entire population of firms. Unfortunately, we do not observe the rate of cash flow burn. Instead, we compare the size of follow-on financing rounds for cloud and non-cloud firms, among those that are already being financed by VCs. In addition to this being a selected sample, follow-on financing rounds depend upon the demand for new financing as well as VC’s willingness to supply funding. We consider the implications of these limitations as we discuss our results below.

Our empirical investigation is based on the subsample of 74 VC-backed firms, from the period after they received the initial round of funding until the end of the sample (i.e., 2009 or the
Our focus on the intensity instead of the incidence of receiving follow-on financing is motivated by the consideration that VCs using staged financing to reduce the potential agency costs will provide more funding rounds, with lower amounts per round (Tian 2011). If cloud firms consume funds more quickly but do not necessarily impose high risks on VCs, we should observe greater follow-on funding for firms that offer cloud products, especially ones that offer both cloud and C/S products.

Because the distribution of follow-on fund size for a firm in a year is highly skewed for the 591 observations by the 74 firms (i.e., with a mean value as $2.367 million but around 75% of the observations equal 0), directly using it as the dependent variable with a linear model would violate the normality assumption on the error term. Thus, we first code the fund size by firm by year as a discrete variable (denoted as \( \text{Follow-on fund size level}_{it} \)), where it equals 0 if a firm in a year did not receive any follow-on funding, 1 if a firm in a year received funding of less than $6.5 million (the 90th percentile of fund size by firm by year), and 2 if a firm received more than $6.5 million in funding. We next employ a random-effects ordered probit model written as: \( \Pr \left( \text{Follow-on fund size level}_{it} = k \mid \mu, X_{it}, v_i \right) = \Pr \left( \mu_k < X_{it} \beta + v_i + \epsilon_{it} \leq \mu_{k+1} \right) \), where funding size level \( k \) equals 0, 1, 2 as defined above; \( X_{it} \beta \) is the set of explanatory variables of interest.

Therefore, \( X_{it} \beta \) can be written as:

\[
X_{it} \beta = \beta_1 \text{Offering cloud}_{it} + \beta_2 \text{Controls}_{it}
\]

Note that our baseline sample (i.e., the one used for Tables 2 to 4) drops all observations for a firm once it introduced the first cloud product. However, in this set of analyses, we do not drop these observations.

We also employed a linear probability model to study the incidence of receiving follow-on funding and found that offering both cloud and C/S products is associated with a greater likelihood of follow-on funding than otherwise.

\( \mu_1 \) and \( \mu_2 \) are the unobserved thresholds and will be estimated as additional parameters of the model, \( \mu_0 \) is defined as \(- \infty\), \( \mu_3 \) is defined as \( + \infty \), \( v_i \) indicates unobserved and time-constant effect for firm \( i \) and is independent of \( X_{it} \). The parameters are then estimated by maximum likelihood method.
We consider the introduction of a cloud product as an absorbing state and thus \( Offering \ cloud_{it} \) will equal 1 from the year that firm \( i \) introduced the first cloud product until the end of the sample and will equal 0 otherwise. In the vector \( Controls_{it} \) we include the full set of controls used in Table 2 (including \( C/S \) product experience, \( Sales \), \( Trademarks \), and \( Patents \)) in addition to the total number of financing rounds that a firm has already received by previous year (denoted as \( No. \ of \ rounds \ by \ previous \ year \)) as well as a complete set of firm age dummies. The estimated coefficient on \( Offering \ cloud \), reported in column (1) in Table 5, is significantly positive, and the estimated probabilities suggest that a firm that offers cloud products would have a 9% (5%) likelihood of receiving follow-on funding at size level 1 (2) in that year whereas a firm that is not offering cloud products has only a 5% (2%) chance of receiving follow-on funding at size level 1 (2) in the same year.

As noted above, firms that produce both traditional C/S products and cloud products at the same time may face several additional challenges that would require even greater financial support from VCs. To test this hypothesis, we again employ a random-effects ordered probit model with the following specification for \( X_{it} \beta \):

\[
X_{it} \beta = \beta_1 Offering \ cloud \ only_{it} + \beta_2 Offering \ C/S \ only_{it} + \beta_3 Offering \ cloud \ and \ C/S_{it} + \beta_4 Controls_{it} \tag{5}
\]

Here we use three dummies—\( Offering \ cloud \ only_{it} \), \( Offering \ C/S \ only_{it} \), and \( Offering \ cloud \ and \ C/S_{it} \)—to indicate whether a firm \( i \) had offered cloud products only, or C/S products only, or both by year \( t \); the vector of \( Controls_{it} \) includes the same set of variables as in equation (4) except \( C/S \) product experience, which captures similar variance as \( Offering \ C/S \ only_{it} \) and thus is dropped. As presented in column (2) in Table 5, the coefficient on \( Offering \ cloud \ and \ C/S \) is significantly positive and greater than the coefficient of \( Offering \ C/S \ only \), though the difference between the
two is insignificant with a \( p \)-value = 0.169. The estimated probabilities suggest that firms doing both would have a 13% (9%) likelihood of receiving funding at size 1 (2), whereas a firm that offers only C/S products would have only an 8% (4%) likelihood of receiving funding at size 1 (2).

Statistical inference in Table 5 should be treated with care because of the small sample size.\(^\text{24}\) In particular, only three firms with six firm-year observations in our sample offer only cloud products, making it difficult to estimate the parameter \( \beta_1 \) in equation (5). As an additional robustness check, we drop the variable \textit{Offering cloud only} \(_{it}\) from equation (5) and rerun the regression, using the entire sample of 74 firms as well as a sample that drops these three firms. The results are reported in columns (3) and (4) respectively. In both cases the coefficient estimate for \textit{Offering cloud and C/S} \(_{it}\) \((\beta_3)\) remains significantly positive and similar in magnitude to column (2); the coefficient of \textit{Offering C/S Only} \(_{it}\) \((\beta_2)\) becomes insignificant, though the difference between \( \beta_2 \) and \( \beta_3 \) remains statistically insignificant with a \( p \)-value of around 0.2.

In regression analyses not shown in the paper due to the limited space, we also find that firms that offer either only cloud products or both cloud and C/S products are not associated with a smaller average funding size per round or with a smaller total funding size. This evidence again suggests that our results do not reflect higher agency costs among cloud product firms. Nevertheless, we acknowledge that our results reflect the equilibrium outcome of VC’s strategic staging behavior and a VC firm’s request for financial resources.

Overall, we show that delivering cloud products is associated with more intensive financing. With some limitations, it provides evidence that cloud firms may require financing in

\(^{24}\) In this sample of 74 firms with a total of 591 firm-year observations, the number of firm-year observations across neither cloud nor C/S, cloud only, C/S only, and both are 105, 6, 354, and 126 respectively.
larger amounts than other VC-backed firms and indicates why such firms may benefit from VC financing.

**Table 5: The interaction between VCs and start-ups during the post-investment stage**

<table>
<thead>
<tr>
<th>Dependent variable: Follow-on fund size level received by firm (i) in year (t)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offering cloud products</td>
<td>0.379*</td>
<td>(0.212)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offering cloud products only</td>
<td>0.834</td>
<td>(0.532)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offering C/S only</td>
<td>0.382*</td>
<td>(0.218)</td>
<td>0.319 (0.207)</td>
<td>0.353 (0.231)</td>
</tr>
<tr>
<td>Offering cloud and C/S products</td>
<td>0.690**</td>
<td>(0.291)</td>
<td>0.608**</td>
<td>(0.274)</td>
</tr>
<tr>
<td>C/S product experience</td>
<td>-0.007</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of rounds by previous year</td>
<td>0.034 (0.043)</td>
<td>0.036 (0.043)</td>
<td>0.031 (0.043)</td>
<td>0.039 (0.043)</td>
</tr>
<tr>
<td>Sales</td>
<td>-0.012 (0.011)</td>
<td>-0.011 (0.012)</td>
<td>-0.011 (0.012)</td>
<td>-0.012 (0.012)</td>
</tr>
<tr>
<td>Trademarks</td>
<td>60.884 (40.685)</td>
<td>46.925 (37.054)</td>
<td>44.692 (37.106)</td>
<td>50.34 (37.492)</td>
</tr>
<tr>
<td>Patents</td>
<td>-0.689 (1.57)</td>
<td>-0.324 (1.488)</td>
<td>-0.371 (1.502)</td>
<td>-0.381 (1.494)</td>
</tr>
<tr>
<td>Age dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of firms</td>
<td>74</td>
<td>74</td>
<td>74</td>
<td>71</td>
</tr>
<tr>
<td>Num. of obs.</td>
<td>591</td>
<td>591</td>
<td>591</td>
<td>563</td>
</tr>
</tbody>
</table>

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

**CONCLUSION**

This paper takes a first step toward closing an important gap in understanding the role that third party organizations play in the evolution of IT platforms. Focusing on the role of VCs, we elaborated in this paper on their role in technology development and shifts in technological trajectories. To do so, we build on the current literature to offer a more nuanced understanding of the role that VCs can play in the creation of new technological ecosystems. In particular, we examine how VCs influence new ventures’ decisions on whether to use new IT platforms. Our key argument is that VCs play an important coordination and instigation roles in the rapid diffusion of new platforms. We argue that, by so doing, VCs can play a critical role in the development of a new technological ecosystem—that is, a paradigmatic shift in the ways in which core computing technologies are used. In their quest for high-value financial exits, VCs invest significant resources in new and unproven technological platforms. In this way, VCs ensure that capital, as well as other necessary resources, are channeled to new businesses that either offer these 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 the ushering in of new technologies.

To empirically check these hypotheses, we looked at complementarities between investing in new—as-yet-unproven—computing platforms by start-ups and VC investment. Focusing our analysis on the period before cloud computing gained acceptance, our results show that VCs have a strong and positive impact on the probability that start-ups will develop a cloud product and that this influence is even more pronounced when the VCs have more technological experience and less pronounced if the start-ups already have significant experience in the old C/S technology. Last, we demonstrate that VC-backed cloud product firms are associated with more intensive financing than other VC-backed software firms.

For practitioners, the paper offers several implications. First, since VCs do play an important (if not necessarily organized or planned) role in technology trajectories and the diffusion of new platforms, policies that encourage interaction and exchange of best practices between VCs, research centers, and prospective entrepreneurs can prove crucial in facilitating the next technological transformation and decrease waste. Second, VCs, especially the high-status and more experienced VCs, which were found to play a more significant role, tend to invest in firms in close proximity to their headquarters. Therefore, localities that wish to play a part in new technological transformation and do not have local high-status experienced VCs should devise ways of ensuring that finance is available to local entrepreneurs that are ahead of the technology acceptance curve. Third, for entrepreneurs, our results provide another perspective on the potential
benefits of location in regions where complementary inputs such as venture financing are available.

Nonetheless, we view this paper as only the first step in a rich empirical investigation on the subject. Hence, much more needs to be done if we are to gain a better understanding of the systemic role of VCs in ushering in new technological trajectories and the micro role of VCs in their invested firms’ product development decisions. A rich first avenue of future research is looking at multiple paradigmatic shifts in computing platforms, which would allow not only a more nuanced understanding but comparison between such shifts that promise to yield a deeper understanding of contextual conditions for the VCs’ role. A second, related, avenue of future research is merging this analysis with economic geography, especially looking at the resurgence of particular locales as dominant regions for new technologies, as well as the ability of others, such as Silicon Valley, to ensure their continued dominance throughout several paradigmatic technological shifts, even as others, such as Boston, stumble. In a similar way, research that aims to compare the rise of new technologies in which VCs do not play such an important role with ICT, such as energy, can yield insights into the limitations of VCs as a coordination and instigation actor in the sponsoring of new technological ecosystems.

The role of third party organizations in the creation of new technologies and industries has by now been widely recognized. Nonetheless, research on the role of VCs, the prominent form of such financial organizations in our age, in IT platforms’ transformations has been thin on the ground. We hope that this paper will inspire further efforts to fill this important gap.

REFERENCES


Hochberg, Y. V., and Rauh, J. D. 2012. Local overweighting and underperformance: Evidence from limited partner private equity investments. Working paper


