PRODUCT MARKET COMPETITION AND CORPORATE VENTURE CAPITAL INVESTMENTS: EVIDENCE FROM THE U.S. IT INDUSTRY

Completed Research Paper

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Abstract

The effect of product market competition on a firm's propensity to use corporate venture capital (CVC) as a viable form of innovation spending is studied in this paper. Using novel measures of product market competition based on product descriptions of firm 10-K statements, we investigate how the product market competition experienced by Information Technology firms in the US during the period 1997-2007 relates to the frequency and magnitude of CVC spending. We find that firms in competitive markets tend to make greater and more frequent CVC investments. Furthermore, we see a shift toward CVC spending and away from R&D investments in competitive markets. In addition, CVC investment appears to be an effective way of exploiting external knowledge for technology leaders, but not for technology laggards. From a methodological viewpoint, we show that text-based network industry classifications, which are extracted from firm 10-K statements, are more informative than three digit SIC classifications in explaining CVC decisions. Finally, using instrumented models, we find some suggestive evidence that high CVC investment can increase product differentiation and reduce ex-post product market competition. Our results provide new insights for theories of innovation and CVC, and also motivate the use of novel measures of product market competition.

Keywords: Product market competition, corporate venture capital, market for technology, absorptive capacity, information technology, R&D, innovation, herding behavior

Introduction

The IT industry is often characterized by intense and rapid technological change (Schmalensee 2000), and fierce product market competition. In particular, frequent and aggressive product market developments by rival firms make this industry one of hyper-competition, where firms must 'move quickly to build an advantage and erode the advantage of rivals' (Lee et al. 2010). In such an industry, the importance of R&D is also well-established (Bettis and Hitt 1995). We test key hypotheses regarding the role of corporate venture capital (CVC) investment in this setting, with a focus on how CVC interacts with changes in product market competition and patent stocks, and how CVC differs from R&D. We examine these links in general, and separately across technology leader and laggard firms. Although CVC is used in other product markets including Bio-Technology, we focus on the IT industry due to the strong foundation established by the existing literature regarding the existence of hyper competition, and strong incentives to invest in innovation.

The acquisition of technological know-how is widely held to be an important source of competitive advantage for firms in technology-based industries facing rapid change (Mowery et al. 1996). However, this rapid change also makes the traditional model of internal research and development (R&D) costly and risky. At stake is the ability to maintain technological leadership. This has led firms to consider alternative methods including CVC for locating and acquiring new technologies. This use of multiple channels to acquire technological knowhow is termed "open innovation" in the literature (Chesbrough 2003). Although CVC is often compared to traditional venture capital (VC), the literature provides strong evidence that they are different (Benson and Ziedonis 2009). VCs are primarily motivated by earning rents on their ability to provide a healthy rate of return to their investors. Although this motive is also present for CVCs, CVCs can also benefit from access to knowledge, especially when it relates to new technologies or products that may change future industry structure (Wadhwa and Kotha 2006). For example, this knowledge sharing may put the firm in a position to acquire the start-up later (Benson and Ziedonis 2009) or to share gains from asset complementarities (Katila et al. 2008). Finally, CVC is particularly appealing in industries with fast-moving technology (Fulghieri and Sevilir 2009).

Our interest in this paper is specific to one such antecedent of CVC that has particular relevance to technology markets – product market competition. Specifically, we are interested in understanding how firms respond to product market competition in their industries by investing in CVC. There is a tradition of research that suggests that competition influences firms' innovation activities, mostly through R&D output (Schumpeter 1942). However, most of this research is set in contexts where the time-line between product development (or R&D) and obsolescence was longer and hence, the impact of immediate product market competition was lower. However, if modern technology markets are characterized by rapid change and therefore, increased product market competition, we should observe greater use of alternative channels of innovation, including CVC investments. This motivates our primary research question: *how does product market competition experienced by the firm influence its CVC activities?*

Although our main focus is on establishing the firm's response to competition through the use of CVC investments, it is also worth asking – does a firm's CVC investments in start-ups actually help the firm differentiate itself in its product market? Prior research suggests that market structure can be influenced by innovative activities of a focal firm (Geroski and Pomroy 1990), specifically by allowing monopoly rents to the innovator (Gilbert and Newbery 1982). In a similar vein, Shaked and Sutton (1987) suggest that R&D and advertising can influence the market structure and competition that a focal firm faces, arguing that advertising and R&D can help the firm endogenously differentiate itself. We argue that in industries with fast-moving technologies, CVC investments provide the firm with a third option for generating for endogenous product differentiation. While providing rigorous empirical evidence for this relationship is challenging, we nevertheless explore the question: *does a firm's CVC investments lead to a reduction in the product market competition faced by the firm in its product markets?*

A primary methodological innovation in our work is to use of new measures of product market competition based on product descriptions of firm 10-K statements. Prior studies generally consider existing industry classifications such as SIC or NAICs, which have inherent limitations in that they are static and rigid (Tang 2006). This can be problematic especially when investigating knowledge-intensive industries where their boundaries are rapidly changing. We consider textual network industry classifications (TNIC) (Hoberg and Phillips 2010a; Hoberg and Phillips 2010b). TNIC industries are based on the product market vocabulary in each firm's 10-K, and firms using highly similar product market vocabularies are classified as being in the same industry. Critical for our agenda to examine the link between CVC and industry change, these classifications are updated every year as 10-Ks are filed annually. Hence, we observe a high level of detail regarding how the product market changes over time.

In addition to the TNIC data, we use VentureXpert to extract information on CVC investments by established firms for the years 1997-2007. We also extract relevant firm-level data from the US Patent Office, Compustat and Lexis-Nexis to assemble a panel dataset on which we conduct our analysis. Our results show that IT firms indeed respond to increased product market competition by increasing their CVC activities. In addition, we also see that firms tend to adjust the mix of R&D and CVC investments per year toward CVC when competition increases, effectively moving a larger proportion of their innovation spending outside the firm. Finally, we show that these effects are much stronger for firms that possess related technology stock, i.e. technology leaders respond to competition by enhancing their CVC investments. Technology leaders, identified as firms with high absorptive capacities or patent stocks, are thus more sensitive to competition and appear to more aggressively invest in CVC to acquire external knowledge. These findings suggest that CVC investment may help technology leaders "escape" product market competition.

Although we also examine whether CVC investments affect product market competition using instrumented models, we expect power to be limited for this test because we have a short panel and product market competition likely changes more slowly than CVC or R&D firm investments. Despite this, we find some suggestive short-run evidence that CVC investments enhance ex-post product differentiation by reducing the extent of rival product similarity surrounding each firm investing in CVC. Our long-run tests produce coefficients that are in the right direction, but results lack statistical significance likely due to the greatly reduced sample size this test entails.

Literature and Hypotheses

Product Market Competition

Since the publication of Schumpeter (1942), the Schumpeterian view is that monopoly power is a precondition for innovation (Gilbert and Newbery 1982; Grossman and Helpman 1991; Schumpeter 1942). A firm with monopoly power faces less market uncertainty, can more easily secure post-innovation monopolistic rents and is less likely to face financial constraints. Alternatively, other studies suggest that innovation increases as competition becomes more fierce (Arrow 1962; Lee and Wilde 1980). Several theoretical papers further suggest that the relationship between competition and innovation is more nuanced and depends on the type of innovation and the definition of industry competition (e.g., Bonnano and Haworth 1998). In addition, empirical evidence is mixed. Nickell (1996) and Blundell et al. (1999) show a positive association between competition and innovation, while Schumpeter (1942) and Tang (2006) report the opposite, and Aghion et al. (2005) find an inverted U-shaped relationship.

Because theoretical motives may vary across markets, we begin by first describing relevant aspects of the IT industry. This industry is characterized by intense and changing competition, where market positions frequently change (Lee et al. 2010). In addition, the industry is characterized by high clockspeed (Mendelson and Pillai 1999) and rapid technological change (Schmalensee 2000). Competitors in the IT industry are aggressive and frequently introduce new products, services or technological platforms, thereby disrupting incumbent platforms and technologies (McAfee and Brynjolfsson 2008). The time interval between new product development and product obsolescence has reduced radically, thereby forcing firms to consider and respond to competition from seemingly unrelated technologies and products. The use of CVC investment is relevant in this setting as it is one channel through which firms can enhance innovation (Chemmanur et al. 2010). Because monopolies are unlikely to persist for a long period of time in this sector, we argue that the "escape competition" effect is likely to dominate the Schumpeterian viewpoint. Hence, firms will react to increased competition by increasing their CVC investments. Thus, we propose the following hypothesis:

H1: As the intensity of the competition in a product market increases, firms increase CVC investment in external ventures.

We further hypothesize that the presence of competition encourages firms to use outside expertise relative to internal R&D resources, ceteris paribus. An extensive literature in the management of innovation addresses the type of cooperation between a downstream firm and its upstream innovator (Aghion and Tirole 1994). Relevant to our study, competition among downstream firms decreases the firm's bargaining power, thereby increasing the attractiveness of independent research activities from the upstream firm's perspective (Aghion and Tirole 1994; Fulghieri and Sevilir 2009). Moreover, intense competition decreases financial slack through lower profitability (Lenox et al. 2010), making firms prefer external investments (such as CVC) to less flexible and expensive internal R&D. On the basis of these arguments, we propose:

H2: As the intensity of the competition in a product market increases, firms increase CVC investment relative to internal R&D investment.

Absorptive Capacity

We postulate that the impact of product market competition on a firm's CVC investment decision depends in part on the *absorptive capacity* of the CVC parent firms. We argue that only technology leaders with strong knowledge base in the related technological space will have an incentive *and* the capacity to search for and exploit CVC opportunities to potentially escape competition. In hyper-competitive markets where products change rapidly, firms with strong prior knowledge stocks will be willing to identify and exploit new innovation opportunities. On the other hand, technology laggards do not have such capabilities to use external innovation opportunities. They are likely to be less active in engaging in CVC activities, since creating or obtaining knowledge through interaction with entrepreneurial firms likely requires a firm to have strong technological expertise in related areas (Dushnitsky and Lenox 2005a). Thus, the effect of competition is likely less pronounced for firms with lower absorptive capacity. This argument also reflects the difference between innovator and imitator strategies (Hellmann and Puri 2000). Innovators create new markets by introducing new products or services. Imitators are also engaged in new markets, but typically not the first in the market. Thus, they tend to compete on aspects other than innovation, such as commercialization and marketing. Therefore, we propose:

H3: The relationship between product market competition and CVC investment is greater for firms that have a stronger base in innovation.

CVC and Change in Product Market Competition

Although work related to Sutton (1991) typically consider R&D and advertising, we propose that CVC investment can also increase product differentiation. CVC investments enable CVC investors to have access to portfolio companies' novel technologies, which can be the basis on which new capabilities are developed by the investors (Benson and Ziedonis 2009). CVC investors can use the capabilities to respond to diverse opportunities, such as developing a new technology and introducing a new product (Dushnitsky and Lenox 2005b). Hence, CVC investments can provide investing firms with wider pool of knowledge than what they have internally, and thereby lead the firms to better position themselves in their product markets by enabling better product differentiation. Therefore, we propose:

H4: As firms increase CVC investment in external ventures, the intensity of the competition in a product market decreases.

Data and Method

Sample Construction

The objective of this analysis is to test the effects of product market competition on the extent to which focal firms invest in CVC. To conduct this analysis, we first construct a dataset of public firms in the U.S. that invested in CVC during the period 1997-2007 from the VentureXpert database. VentureXpert provides detailed information on entrepreneurial ventures which have been funded by independent venture capitalists as well as corporate investors, along with other funding information such as the round of funding and the relative amounts of money received from each investor. We collect data for all corporate investors who actually funded CVC, and we thus extract the identities of the potential CVC firm therein. We create a a list of 800 potential CVC firms. Using various sources of information (Google, Lexus/Nexus, etc.), we then manually identify those with a corporate parent. We drop the firms that represent financial companies, partnerships, funds, or those with an unknown parent. This leaves us with 326 distinct CVC parent firms out of which 145 are publicly traded US IT firms. We also exclude CVC firms that have a foreign parent. We include other years in the study period without any CVC investment for each firm after the first year in which it is observed to invest in CVC. Periods before the first observation of a CVC investment are omitted since it is not clear whether the firm possessed any interest in CVC in these periods. Our final sample thus comprises 1049 firm-year observations by 143 firms during the period 1997-2007. This provides us with a set of CVC firms we consider to be our primary database. To this data, we add relevant information from other sources as described below.

For each corporate CVC investor-year observation, we also require information on the product market competition faced by the given CVC investor. Therefore, we augment the baseline database with dynamic Text-based Network Industry Classification (TNIC) data from Philips and Hoberg (2010a, 2010b), which is described indetail in the below section. To access investor firm-level financial and organizational data, we use Compustat. We also use the CRSP database to obtain monthly stock returns for the CVC investors for the years in our analysis. Finally, in order to capture the level of technological expertise resident in the firm in a given year, we collect patent data from the NBER patent citation database (see Hall et al. (2001) for more details). The database provides detailed information on U.S. patents granted between 1976 and 2006, including the application and grant year, assignee identifier, and main U.S. patent class. Consistent with the literature, we use the application year rather than the grant year for patent activity by year, since it takes more than two years to get a patent granted. The application date is hence closer to the actual innovation. This combined database provides us with an unbalanced panel of firm-year-CVC investments, describing the extent to which firms allocate innovation dollars to CVC in a given year. We discuss the individual variables in detail below.

Variables

We create our three dependent variables to proxy for annual CVC activities. The first dependent variable is the annual amount of CVC investment (Dushnitsky and Lenox 2005a). The second is a dummy variable which is equal to 1 if a firm invested CVC at a given year. The last is the number of CVC round financing. Staged financing is a key mechanism a venture capitalist can employ to monitor its portfolio firms (Gompers 1995). It helps corporate investors spread their money to many start-ups. Although there is some overlap among these measures, they provide some unique industry features and enhance the robustness of our findings. Following prior work (Blundell et al. 1999; Dushnitsky and Lenox 2005a), we use patent stock to capture technological capability of each CVC parent firm. The patent stock is calculated by the sum of last year's patent stock and current year's number of patents applied.

$$\text{Patent stock}_{it} = \text{Number of patent}_{it} + (1 - \delta)\text{Patent stock}_{it-1}$$

where δ is the rate of stock depreciation. Each patent is depreciated at a rate of 15% and thus, older patents have lesser impact on the firm's patent stock than recent patents.

In addition, we use the COMPUSTAT database to obtain firm-specific financial variables. CRSP is also used to obtain the standard deviation of monthly stock returns as a proxy for market uncertainty (Bloom et al. 2007). Our key control variables are *firm size*, *free cash intensity*, *R&D intensity*, and *sales growth*, consistent with prior work (Benson and Ziedonis 2009; Dushnitsky and Lenox 2005a). Our key independent variables are competition variables based on the new TNIC data. Since our TNIC-based competition variables are new, we explain in detail those variables in the next section.

Text-based Product Market Variables

This section describes the TNIC data that we use to capture product market competition in our analysis, based on work by Hoberg and Philips (henceforth ``HP', see Hoberg and Phillips (2010a, 2010b) for more details). These variables are purely based on business descriptions of firm 10-K statements. As a first step, HP use text mining techniques to construct a database of business descriptions from 10-K annual filings on the SEC's Edgar website from 1997 to 2008. The business description, which can generally be found in Item1 or Item 1A of the 10-K is parsed to separate it from the the rest of the 10-K. The business description is legally required to be accurate and up-to-date and in aggregate, these filings depict the current competitive environment surrounding each firm.

To form industry classifications from this textual data, HP first form a Boolean word vector fully describing the words used by each firm. To emphasize product vocabulary, only nouns and proper nouns are used to construct these vectors, and common words (used in more than 25% of all business descriptions in a given year) are discarded[1]. These vectors are then used to compute cosine similarities for every pair of firms that measure the extent

[1] See HP for details regarding robustness. Boolean word weights are used instead of frequency weights due because the distribution of usage across words is extreme, and frequency weights reduce informativeness. HP also indicate that TNIC links are purged of vertical relatedness as identified by the BEA Input Output tables. Results are also robust to variations in the stop word threshold, or to including all words instead of nouns and proper nouns only.

to which firms use similar product market vocabulary. Cosine similarities are bounded in interval [0,1] and will approach 1 if two firms have similar products. Cosine similarities are commonly used in studies of information processing (see Sebastiani (2002) for a review of methods).

TNIC industries are formed using the resulting firm-by-firm pairwise cosine similarity matrix. This similarity matrix is analogous to a network identifying product market relatedness. A given firm A's industry is composed of firms whose product similarity to firm A exceeds a threshold. The threshold is chosen such that the TNIC industry granularity matches that of three digit SIC codes. The central advantage that the TNIC provides is that the focal firm's competitive industry changes every year since the firm's product description changes, as do the product descriptions of other firms that may either enter or exit the focal firm's industry in a given year. Compared to the static SIC or NAICS codes, the use of TNIC thus allows us to observe year on year changes to any focal firm's market structure. TNIC industries also relax the transitivity property of SIC codes, allowing us to improve power and measure competition strictly relative to a given firm, rather than at the level of the industry or SIC code.

The total similarity of firm A is defined as the sum of product market similarities relative to firm A across firms within its TNIC industry. Higher total similarity implies more competition within the firm's TNIC. In addition, we include the total number of firms operating in the focal firm's TNIC per year. The greater the number of firms found in the focal firm's TNIC in a given year, the greater the product market competition experienced by that firm. We believe that new TNIC3-based competition measures are more informative in explaining CVC investments, because typical measures for industry structure, such as LI and the Herfindahl-Hirschman Index (HHI), are measured based on past performance, while our two competition variables represent forward-looking competitive threats. Nevertheless, we include industry LI for comparison with prior papers. We do not consider HHI measures of product market competition in this study due to the unique high growth nature of the IT industry and hence the irrelevance of current sales. For example, the winner-take-all phenomenon isa salient issue in the IT industry. As a result, HHI measures, which are based on squared market shares, can be large even when large numbers of rivals exist. In unreported tests, we confirm that HHI measures are uninformative in this setting. Economically, this suggests that the existence of a rival firm with good technology in this setting is more important than the given rival's sales. We calculate our industry Lerner Index based on the price cost margin in the following way (Aghion et al. 2005). Higher industry LI indicates more competition. Since a focal firm has its own industry, these industry-level variables are not the same for firms within a focal firm's industry. This characteristic does not apply to the traditional industry classification such as SIC and NAICS in that all firms in the same industry (e.g., SIC 730) have the same competition measures.

Empirical Model

We consider the joint endogeneity between competition and innovation activity. A system of two equations is estimated to explore this relationship. The base model for testing the impact of competition on CVC activities is:

$$\text{CVC activity}_{it} = \beta_0 + \beta_1 * \text{PMC}_{it-1} + \beta_2 * X_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it} \qquad (1)$$

where the subscript represents firm i in year t. We use three variables for CVC investments: Annual CVC amount, CVC dummy, and number of CVC financings. PMC represents text-based competition variables of each firm, and X includes vectors of firm-specific characteristics that potentially affect the CVC investments and the propensity to invest CVC. α_i and α_t are firm- and time-fixed effects. We use lagged variables as our independent variables. This is likely to better reflect a firm's search process for innovation (e.g., Blundell et al. 1999) and helps to dampen possible endogeneity issues. We apply dynamic panel data models (Arellano and Bond 1991; Blundell and Bond 1998) to estimate this equation. We conduct Blundell and Bond "System" GMM estimation which uses both lagged levels and differences as internal instruments. Since too many instruments can lead to a finite sample bias and suspiciously high pass rates of specification tests like the Hansen J-test, we follow Roodman (2009) and use only certain lags region for the system GMM. To construct instruments, we use lags 1 and 2 of competition and patent stock variables for the transformed equation and lag 0 of the same variables in differences for the levels equation. We use only lag 1 of the other variables for the first-differenced data, with the exception of CVC experience and year dummies.[2] CVC experience and year dummies are thus assumed to be exogenous. Using the Hansen test, we check the validity of moment conditions and of additional moment restrictions required by the system GMM (Blundell and Bond 1998; Roodman 2009). For purposes of comparison, we also consider ordinary least squares

[2] Our results are robust to alternative lag structures.

regression for the annual CVC amounts, and the logistic regressions where the dependent variable is a dummy for the presence (absence) of CVC investment in that year. Since the number of CVC round financings is a count variable, we consider negative binomial regressions for this variable.

To estimate the impact of CVC investment on competition we regress the change in competition on various determinants of competition, including CVC investment (Geroski and Pomroy 1990). The second equation for this is as follows:

$$\Delta PMC_{jt} = \beta_0 + \beta_1 * CVC_{jt-1} + \beta_2 * Z_{jt-1} + \delta_j + \delta_t + e_{jt} \qquad (2)$$

where the subscript represents industry j in year t. Z include vectors of other industry-specific variables that potentially affect the level of competition. In our paper we include R&D investments and advertising expenses. The lagged dependent variables are included on the right-hand side of some specifications to capture persistence in competition and also potentially mean-reverting dynamics in competition (i.e., the tendency of the competition level to return to some short-run equilibrium value for a firm). We conduct both OLS and IV regressions at the industry level, since the level of competition facing a given firm will be determined by both its investments and its direct competitors' investments.[3] In the IV regressions, we instrument for CVC investment of a focal firm as the average CVC investment of other firms operating in the same industry with each firm competing in a focal firm's industry except the focal firm's direct competitors.

Results

Summary Statistics

To minimize potential effects of outliers, we winsorized free cash intensity and R&D intensity at the top and bottom fifth percentiles in our analysis and log-transformed some other key variables, including annual CVC amount, industry LI, firm size, and patent stock. The mean level of the annual CVC investment is $65.8 million, which is based on the panel data and includes years with no CVC investment. If we consider just years with some CVC investment, the mean value of the annual CVC amount is $139.5 million. For reference, the mean R&D expenditure in our sample is $480.4 million. The CVC amount made by firms in our sample exhibits a wide variation in the magnitude from 0 to $5.6 billion. The average number of annual CVC round investments is 2.96, while the maximum number is 215. The median TNIC3-based LI is 1.40 while the median total product similarity is 345.6. The median total product similarity for the entire TNIC data is 217.42, implying that our sample firms face significantly higher competition. The median and maximum numbers of firms within a TNIC-based industry are 93 and 522, respectively. The mean total number of years since the first CVC investment is 6. We construct this variable by searching for CVC investments since 1970. The earliest CVC investment was in 1974 in our sample.

Multivariate Evidence

The CVC activities

Panel A of Table 1 presents the results of conducting multivariate analysis where the dependent variables are annual CVC investment, CVC dummy and number of CVC round financing respectively. The results in columns (1)-(3) indicate that firms in competitive markets are likely to increase the amount of annual CVC investments. Three competition variables are statistically significant and positive at least at the 5% level. The positive impacts of competition on CVC activities also hold for the propensity of CVC and the number of CVC financing (see columns (4)-(9)). Thus, the results strongly confirm Hypothesis 1 predicting a positive association between competition and CVC investments, providing evidence for the "escape competition" argument (Aghion et al. 2005).

Competition can be influenced by innovation activity like CVC investment, which means competition can be endogenous. Thus, we also apply dynamic panel data models (Arellano and Bond 1991; Blundell and Bond 1998). We conduct Blundell and Bond "System" GMM estimation which uses both lagged levels and differences as internal instruments. Panel B of Table 1 reports the two-step system GMM estimates. Using the Hansen test, we check the validity of moment conditions and of additional moment restrictions required by the system GMM (Blundell and

[3] We conduct the IV regression instead of dynamic panel data model here, since we found that the dynamic panel data model is too sensitive to get reliable and robust results. The results depend too much on how many lags we use as instruments.

Bond 1998). The results are qualitatively similar to them shown in Panel A, but are weak. We found a robust evidence that intense competition leads to larger amount of CVC investments. Higher product market similarity further increases the number of CVC round financing, while other two competition variables are not statistically associated with other CVC activities. This might be partly because we treat CVC dummy and the number of CVC round financing as a continuous variable. On the other hand, in Panel A we have exploited the different nature of variables by conducting the logistic regression for CVC dummy and the negative binomial regression for the number of CVC round financing.

We also find that the positive relationships between market uncertainty (i.e., standard deviation of monthly stock returns) and CVC investments are robust when we account for endogeneity. This shows that uncertainty makes CVC investment more preferred than R&D investment, suggesting that the flexibility of CVC is more valuable in uncertain markets. This is consistent with real options investment theory that greater uncertainty about market conditions may reduce current investment in more irreversible capital by increasing the value of waiting (Bloom et al. 2007; Dixit and Pindyck 1994). Furthermore, big firms tend to invest CVC more even after accounting for their financial and technological strengths. This suggests that investing in startups might require extra capabilities beyond cash and technological capabilities, like working with entrepreneurial firms within their venture portfolios (Benson and Ziedonis 2009). We mostly find expected signs for other controls, although not robust.

Table 1 also investigates whether firms prefer external CVC investments to internal R&D investments in competitive markets (see columns (10)-(12)). The dependent variable here is the logged value of the ratio of CVC spending per year to the total spending on innovation (CVC + R&D), to capture the relative attractiveness of CVC versus R&D. The results indicate positive association between product market similarity and the ratio of CVC to total innovation spending, which supports Hypothesis 1a. High product market similarity drives firms to prefer external innovation opportunities to internal R&D sources. Number of firms and industry LI also have expected signs, but are not significantly associated with the ratio of CVC in the system GMM specifications.

Table 2 tests more nuanced predictions related to technological capability. We divide the data into two subsamples based on a proxy for firm absorptive capacity- patent stock. Patent stock is a reasonable measure for firm knowledge capital since patents represent the success of an internal R&D program. To the extent that the tendency of a firm to apply for a patent varies across the IT industries, however, the number of patent stock might reflect some institutional features of the industries (Hall et al. 2001). Therefore, we include industry dummies based on the one digit SIC code.

We use these subsamples to test the hypothesis that the effect of competition on CVC investment varies between technology leaders and laggards. We present the findings in Panel A of Table 2 using the annual amount of CVC investment as a dependent variable. We generally find that the role of competition is especially pronounced for technology leaders. This result is consistent with firms wanting to sustain their technological leadership, which could be lost in highly competitive markets. Also, they are likely to know how to select better portfolio companies with their strong technology base. On the other hand, technology followers show no significant reaction to competition in their budget for CVC activities, even though they have invested in CVC in the past to appear in our sample. Since we control for firm size and free cash intensity, these findings are likely not driven by differences in financial conditions between technology leaders and laggards. It is however possible that technology laggards use a different set of expertise (other than technology-specific knowledge stock) such as manufacturing capabilities and commercial capabilities (Hellmann and Puri 2000) to be competitive. Thus, they are less sensitive to competition in terms of technology acquisition.

Furthermore, Panel B of Table 2 shows another evidence of the difference in what drives CVC investments between technology leaders and laggards. When including one-year lagged average CVC intensity of other firms in an industry, we find that only CVC investors with weak absorptive capacity might follow the investment decisions of other CVC investors. Results from the system GMM show that one-year lagged industry average CVC intensity is positively associated with a firm's CVC activities at the current year for only technology laggards, even after controlling for general competition. When other firms in an industry are adopting CVC strategies, managers in a technologically weak firm might face more scrutiny if their failed CVC strategy deviates from rival strategies (Scharfstein and Stein 1990). However, it seems that technology leaders show little herding behavior in terms of CVC investments and their CVC investments are mostly driven by competitive pressure in product markets. Even though we do not report, the overall impact of one-year lagged industry average CVC on a given firm's CVC investment is positive and significant.

Table 1 Product market competition and CVC investments

Panel A												
	Ln(CVC amount)			*CVC dummy*			*Number of CVC round financing*			*LN(CVC / (R&D+CVC))*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TNIC3 total similarity /1000	0.529***			0.606***			0.405**			0.861***		
	(0.194)			(0.230)			(0.173)			(0.293)		
TNIC3 number of firms		0.002**			0.002*			0.002***			0.003**	
		(0.001)			(0.001)			(0.001)			(0.001)	
Ln(TNIC3 Ind LI)			0.288***			0.311*			0.284***			0.573***
			(0.108)			(0.164)			(0.080)			(0.214)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1049	1049	1049	1049	1049	1049	1049	1049	1049	1049	1049	1049
(Pseudo) R-squared	0.39	0.39	0.39	0.24	0.23	0.24				0.30	0.30	0.30
Panel B (System GMM)												
TNIC3 total similarity /1000	0.656**			0.088			0.262*			0.936*		
	(0.292)			(0.080)			(0.155)			(0.561)		
TNIC3 number of firms		0.002*			0.000			0.001			0.002	
		(0.001)			(0.000)			(0.001)			(0.002)	
Ln(TNIC3 Ind LI)			0.196			0.026			0.072			0.333
			(0.144)			(0.040)			(0.053)			(0.289)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	996	996	996	996	996	996	995	995	995	996	996	996

Note: Panel A of the table reports OLS regression for *Ln(CVC amount)*, logistic regression for *CVC dummy* and negative binomial regression for *number of CVC round financing* using lagged independent variables. Standard errors are clustered by firms. Panel B of the table reports two step system GMM estimation using lagged independent variables. The estimates are Windmeijer corrected for robust standard errors. We use lags 2 through 3 of the levels as instruments of competition and patent stock for the first-differenced data and, as instruments, lag 2 alone for the others for the first-differenced data except for CVC experience and year dummies. CVC experience and year dummies are assumed to be exogenous. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 2 Technology leaders versus laggards (DV: Ln(CVC amount))												
Panel A												
	OLS						System GMM					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Leader	Laggard	Leader	Laggard	Leader	Laggard	Leader	Laggard	Leader	Laggard	Leader	Laggard
TNIC3 total similarity/1000	0.889***	-0.190					1.307**	-0.201				
	(0.249)	(0.295)					(0.522)	(0.503)				
TNIC3 number of firms			0.004***	-0.001					0.005**	-0.001		
			(0.001)	(0.001)					(0.002)	(0.005)		
Ln(TNIC3 Ind LI)					0.410***	0.042					0.405	-0.047
					(0.115)	(0.166)					(0.277)	(0.196)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	575	474	575	471	575	471	538	458	538	458	538	458
R-square	0.43	0.47	0.43	0.47	0.42	0.47						
Panel B : Include industry-level CVC intensity												
TNIC3 total similarity/1000	0.875***	-0.248					1.405***	-0.235				
	(0.255)	(0.277)					(0.487)	(0.382)				
TNIC3 number of firms			0.004***	-0.001					0.005**	-0.001		
			(0.001)	(0.001)					(0.002)	(0.002)		
Ln(TNIC3 Ind LI)					0.019**	0.012					0.294	-0.022
					(0.008)	(0.013)					(0.284)	(0.203)
Ln(Industry CVC intensity)	0.029	0.056	0.005	0.057	0.059	0.049	-0.001	0.140***	-0.031	0.137***	0.039	0.102**
	(0.053)	(0.047)	(0.056)	(0.047)	(0.053)	(0.048)	(0.104)	(0.047)	(0.093)	(0.046)	(0.046)	(0.041)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	538	458	538	458	538	458	538	458	538	458	538	458

Note: The table reports OLS and two step system GMM estimation using lagged independent variables. The estimates are clustered by firms for OLS and Windmeijer corrected for system GMM. We use lags 2 through 3 of the levels as instruments of competition and patent stock for the first-differenced data and, as instruments, lag 2 alone for the others for the first-differenced data except for CVC experience and year dummies. CVC experience and year dummies are assumed to be exogenous. For ease of presentation, we omit other firm-specific characteristics. *** significant at 1%; ** significant at 5%; * significant at 10%

Comparison with traditional SIC-based competition

We examine whether SIC-based market structure measures differ from our text-based measures in explaining CVC investment. Arguably, this is the core contribution of the TNIC-based competition measures. In the IT industry, the mean of industry LI is smaller for the TNIC3 data than for SIC3 data, which implies lower competition level in the TNIC3 data. Text-based industries generally have smaller number of firms because competitors in these markets are more localized than what SIC3 suggests. Finally, text-based industries show greater change in industry LI and the number of firms, indicating that the text-based industry classification is better at tracking real change in market structure, compared to static SIC-based industry classification.

The results show that the competition measures based on SIC3 are not significantly associated with CVC investment, which is markedly different from what was obtained using TNIC data (unreported, available upon request). We further test the difference in the effects between technology leaders and laggards using SIC3. The traditional SIC3-based measures are only significant for technology laggards, which is again contrary to the results observed from the TNIC data. In the absence of dynamic text-based data, one would draw the wrong conclusions on the relationship between product market competition and CVC investments through the use of SIC3 data. However, in the presence of intense competition, the TNIC-based measures are more applicable since they more accurately capture the true competitive pressures felt by focal firms. Our evidence shows that competition measures based on the TNIC-based industry classification appear to better explain firm CVC activities than those based on the SIC classification.

Additional tests

One possible source of bias in our results arises from possible firm-specific unobserved heterogeneity, although year fixed-effects are included to account for macroeconomic trends that might affect the overall CVC investment.[4] Hence, we re-estimate our models while including firm fixed effects to control for unobserved, time-invariant firm-level characteristics. We find that more competition still drives firms to put more money on CVC. Omitted variables bias likely is not a serious problem in our study.

We also examine whether the impact of product market competition on CVC investments might reflect more underlying effects from technological opportunities (Levin et al. 1985). To control for technological opportunities at the industry level, we use the average citations within a firm's industry in a given year (Dushnitsky and Lenox 2005a). We obtained qualitatively similar results to those in Table 1. Thus, technological opportunities likely do not drive our results.

The Impact of CVC investment on competition

Although examining the effect of competition on CVC investment is the central focus of our paper, we also investigate the hypothesis that product market competition is influenced by investments in CVC. Firms that succeed in innovating tend to grow and differentiate their products, resulting in increased market shares and profits. Hence, investments in startups might help CVC investors to exploit novel technologies from startups and have a temporal monopoly position in a differentiated market.

Table 3 shows the short-run impact of investments on change in competition. The results indicate that industry-level CVC investments are likely to decrease the level of product similarity in the short run (see columns (1), (4), (7) and (12)). Investments in CVC appear to make firms differentiate their products from their competitors' and, thereby, operate in a less competitive market. On the other hand, the impacts of CVC on other two competition variables are not robust between two IV regressions, although we have expected, negative signs for the number of firms. Interestingly, we find more persistency of forward-looking competitive threats (i.e., product similarity and number of firms) than that of the history-based market structure (i.e., industry LI) (see columns (4)-(6) and (10)-(12)). This implies that some industries by nature might attract many competitors because of strong technological opportunities and other factors, but at the same time these industries might be more turbulent in that top-selling companies one year may not dominate the next (McAfee and Brynjolfsson 2008).

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[4] When we conduct the system GMM, we use the first-difference to remove possible firm-specific unobserved characteristics. Since the system GMM relies on strong assumptions, estimating fixed-effects models is useful to establish the robustness of our results.

We also tested long-term impacts of CVC investment on competition and got the expected, negative signs for CVC investments with results not significant likely due to low power. The power is very low for long-term tests because of short sample and few observations. But, we note that the OLS results are significant, although instrumentation reduces power. We omit the results from the paper to conserve space and we leave the long-term analysis to future research as more data becomes available.

Conclusions

In this paper we examine the relationship between product market competition and CVC investment. Building on prior literature on competition and innovation, we show that competition affects firm-level CVC decisions in the hypercompetitive IT industry in four ways. First, we find a significant association between product market competition and CVC investments especially in the software industry. Firms further prefer CVC investments to internal R&D investments in competitive industries. In addition, we shed light on the role of prior related knowledge of CVC investors in providing insights on the “competition effect”. CVC investments may be an effective way of escaping competition for technology leaders, but not for technology laggards. Third, the impact of product market competition is stronger when uncertainty is larger. Finally, we find that industry-level CVC investments decrease the level of product similarity among firms at least in the short run.

Our study has useful implications for firm innovation decisions. First, our research adds to the literature on innovation using firm-centric competition measures. Most empirical studies that examine the relationships between competition and innovation have focused often on industry concentration measured at the traditional static industry systems. However, the industry classifications have been challenged, since different firms might have different perceptions about the level of competition they are facing (Tang 2006). This is especially important for research examining knowledge-intensive industries, since those industries are rapidly transforming and their boundaries are blurring. Thus, the traditional SIC systems are less likely to provide timely information on the nature of competition in those industries. Thus, our findings that the TNIC-based measures are better in predicting firm CVC decisions than the SIC-based measures should encourage researchers to consider this data to examine the role of competition in other contexts.

In addition, our study contributes to the literature on corporate entrepreneurship by shedding new light on the role of CVC investments as a product differentiation strategy. Past literature identified several strategic benefits of CVC investments, such as better identification of promising startups (Benson and Ziedonis 2009) and higher innovation rates through access to novel technologies owned by portfolio companies (Dushnitsky and Lenox 2005b; Wadhwa and Kotha 2006). By providing evidence that CVC investments can enable CVC investors to differentiate their products from their competitors', our study suggests that CVC investments can also dampen product market competition.

The findings provide practical implications for CVC investors in technology-intensive industries. Our findings suggest that, in competitive markets, firms are highly sensitive to the selection and coordination of innovation inputs. When firms face rapid technological change and uncertainty about competitive environments, firms turn to external innovation channels to be competitive and actually succeed in dampen competitive threats. Furthermore, the shift toward external knowledge sources increases in the presence of strong internal knowledge capabilities. The findings suggest that firms, especially with strong knowledge base, can escape competition with effective use of external knowledge sources.

Furthermore, our study supports the validity of open innovation models and hence suggests that firms should experiment and adopt different forms of open innovation models. This is further true because the success of open innovation can differ across technologies and industries. CVC investments might not be helpful for firms operating in non-IT industries to dampen competitive threats. Even in the IT industry technology laggards are less active in CVC activities than technology leaders. Thus, it appears important that firms should look for appropriate forms of open innovation for their businesses.

Table 3 Short-run impact of investments on change in competition												
	OLS			OLS			IV			IV		
	Δsimilarity	Δ# of firms	ΔInd LI	Δsimilarity	Δ# of firms	ΔInd LI	Δsimilarity	Δ# of firms	ΔInd LI	Δsimilarity	Δ# of firms	ΔInd LI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Industry-level CVC investment)	-8.433***	-2.414***	0.059	-1.189	0.601	-0.383*	-50.693**	-6.886*	0.150	-42.621*	-0.387	-2.243*
	(2.908)	(0.536)	(0.124)	(5.507)	(0.621)	(0.209)	(21.391)	(3.931)	(0.938)	(23.353)	(3.844)	(1.231)
Ln(Industry-level RD investment)	-0.321	-0.368	-0.427	10.044	2.720**	0.833*	23.218	0.876	0.169	35.411**	3.437	3.358***
	(5.526)	(1.244)	(0.339)	(6.849)	(1.072)	(0.450)	(17.058)	(3.468)	(0.795)	(17.758)	(2.607)	(1.189)
Ln(Industry-level Adv. investment)	-8.776***	-2.730***	-0.529**	-3.688	-0.781	0.023	5.563	-2.460	-0.460	23.161	2.883	0.702
	(3.006)	(0.805)	(0.264)	(2.644)	(0.694)	(0.118)	(14.982)	(2.325)	(0.506)	(17.087)	(2.211)	(1.158)
TNIC3 total similarity				-0.188***						-0.176***		
				(0.050)						(0.048)		
TNIC3 number of firms					-0.209***						-0.216***	
					(0.018)						(0.028)	
TNIC3 ind LI						-0.632***						-0.871***
						(0.213)						(0.227)
Adj R-squared	0.0697	0.0885	0.0209	0.2057	0.2397	0.2794						
Observations	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112

Note: The table reports OLS regression and IV regression for *change in competition* using one year-lagged independent variables. Instruments for a focal firm's industry are average investments of other firms operating in the same industry with each firm competing in a focal firm's industry except the focal firm's direct competitors. Standard errors are clustered by firms. *** significant at 1%; ** significant at 5%; * significant at 10%

References

Adner, R., and Levinthal, D. 2001. "Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation," *Management Science* (47:5), p. 611.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. 2005. "Competition and Innovation: An Inverted-U Relationship," *Quarterly Journal of Economics* (120:2), pp. 701-728.

Aghion, P., and Tirole, J. 1994. "The Management of Innovation," *The Quarterly Journal of Economics* (109:4), November 1, 1994, pp. 1185-1209.

Arellano, M., and Bond, S. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* (58:194), p. 277.

Arora, A., and Ceccagnoli, M. 2006. "Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing," *Management Science* (52:2), pp. 293-308.

Arrow, K. 1962. "Economic Welfare and the Allocation of Resources for Invention." National Bureau of Economic Research, Inc, pp. 609-626.

Benson, D., and Ziedonis, R.H. 2009. "Corporate Venture Capital as a Window on New Technologies: Implications for the Performance of Corporate Investors When Acquiring Startups," *Organization Science* (20:2), pp. 329-351.

Bessen, J., and Maskin, E. 2009. "Sequential innovation, patents, and imitation," *The RAND Journal of Economics* (40:4), pp. 611-635.

Bettis, R.A., and Hitt, M.A. 1995. "The New Competitive Landscape," *Strategic Management Journal* (16), pp. 7-19.

Bloom, N., Bond, S., and Reenen, J.v. 2007. "Uncertainty and Investment Dynamics," *The Review of Economic Studies* (74:2), pp. 391-415.

Blundell, R., and Bond, S. 1998. "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics* (87:1), pp. 115-143.

Blundell, R., Griffith, R., and Van Reenen, J. 1999. "Market share, Market Value and Innovation in a Panel of British Manufacturing Firms," *Review of Economic Studies* (66:228), pp. 529-554.

Bonanno, G., and Haworth, B. 1998. "Intensity of competition and the choice between product and process innovation," *International Journal of Industrial Organization* (16:4), pp. 495-510.

Chemmanur, T.J., Loutskina, E., and Tian, X. 2010. "Corporate Venture Capital, Value Creation, and Innovation," *Boston College Working Paper*).

Chesbrough, H.W. 2003. *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Harvard Business Press.

Dixit, A.K., and Pindyck, R.S. 1994. *Investment under Uncertainty*. Princeton University Press.

Dushnitsky, G., and Lenox, M.J. 2005a. "When Do Firms Undertake R&D by Investing in New Ventures?," *Strategic Management Journal* (26:10), pp. 947-965.

Dushnitsky, G., and Lenox, M.J. 2005b. "When do incumbents learn from entrepreneurial ventures? Corporate venture capital and investing firm innovation rates," *Research Policy* (34:5), pp. 615-639.

Fulghieri, P., and Sevilir, M. 2009. "Organization and Financing of Innovation, and the Choice between Corporate and Independent Venture Capital," *Journal of Financial & Quantitative Analysis* (44:6), pp. 1291-1321.

Geroski, P.A., and Pomroy, R. 1990. "Innovation and the Evolution of Market Structure," *Journal of Industrial Economics* (38:3), pp. 299-314.

Gilbert, R.J., and Newbery, D.M.G. 1982. "Preemptive Patenting and the Persistence of Monopoly," *The American Economic Review* (72:3), pp. 514-526.

Gompers, P.A. 1995. "Optimal Investment, Monitoring, and the Staging of Venture Capital," *Journal of Finance* (50:5), pp. 1461-1489.

Grossman, G.M., and Helpman, E. 1991. "Quality Ladders in the Theory of Growth," *Review of Economic Studies* (58:193), p. 43.

Hall, B.H., Jaffe, A.B., and Trajtenberg, M. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." NBER Working Paper No. 8498.

Hellmann, T., and Puri, M. 2000. "The interaction between product market and financing strategy: the role of venture capital," *Review of Financial Studies* (13:4), Winter2000.

Hoberg, G., and Phillips, G. 2010a. "Dynamic Text-based Industry Classifications and Endogeneous Product Differentiation " *University of Maryland Working Paper*).

Hoberg, G., and Phillips, G. 2010b. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis," *Review of Financial Studies* (23:10), pp. 3773-3811.

Katila, R., Rosenberger, J.D., and Eisenhardt, K.M. 2008. "Swimming with Sharks: Technology Ventures, Defense Mechanisms and Corporate Relationships," *Administrative Science Quarterly* (53:2), pp. 295-332.
Lee, C.-H., Venkatraman, N., Tanriverdi, H., and Iyer, B. 2010. "Complementarity-based hypercompetition in the software industry: Theory and empirical test, 1990–2002," *Strategic Management Journal* (31:13), pp. 1431-1456.
Lee, T., and Wilde, L.L. 1980. "Market Structure and Innovation: A Reformulation," *The Quarterly Journal of Economics* (94:2), pp. 429-436.
Lenox, M.J., Rockart, S.F., and Lewin, A.Y. 2010. "Does interdependency affect firm and industry profitability? an empirical test," *Strategic Management Journal* (31:2), pp. 121-139.
Levin, R.C., Cohen, W.M., and Mowery, D.C. 1985. "R & D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses," *The American Economic Review* (75:2), pp. 20-24.
McAfee, A., and Brynjolfsson, E. 2008. "Investing in the IT That Makes a Competitive Difference," *Harvard Business Review* (86:7/8), pp. 98-107.
Mendelson, H., and Pillai, R.R. 1999. "Industry Clockspeed: Measurement and Operational Implications," *Manufacturing Service Operations Management* (1:1), January 1, 1999, pp. 1-20.
Mowery, D.C., Oxley, J.E., and Silverman, B.S. 1996. "Strategic Alliances and Interfirm Knowledge Transfer," *Strategic Management Journal* (17), pp. 77-91.
Roodman, D. 2009. "How to do xtabond2: An introduction to difference and system GMM in Stata," *Stata Journal* (9:1), pp. 86-136.
Scharfstein, D.S., and Stein, J.C. 1990. "Herd behavior and investment," *American Economic Review* (80:3), p. 465.
Schmalensee, R. 2000. "Antitrust Issues in Schumpeterian Industries," *American Economic Review* (90:2), pp. 192-196.
Schumpeter, J.A. 1942. *Capitalism, Socialism and Democracy*. New York: Harper & Row.
Sebastiani, F. 2002. "Machine learning in automated text categorization," *ACM Computing Surveys* (34:1), pp. 1-47.
Shaked, A., and Sutton, J. 1987. "Product Differentiation and Industrial Structure," *Journal of Industrial Economics* (36:2), pp. 131-146.
Tang, J. 2006. "Competition and innovation behaviour," *Research Policy* (35:1), pp. 68-82.
Wadhwa, A.N.U., and Kotha, S. 2006. "Knowledge Creation Through External Venturing: Evidence from the Telecommunications Equipment Manufacturing Industry," *The Academy of Management Journal* (49:4), pp. 819-835.
Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.