Rev Ind Organ (2015) 46:323–347
DOI 10.1007/s11151-015-9462-3

Specialization and Competition in the Venture Capital Industry

Yael V. Hochberg[1] · Michael J. Mazzeo[2] · Ryan C. McDevitt[3]

Published online: 9 April 2015

Abstract An important type of product differentiation in the venture capital (VC) market is industry specialization. We estimate a market structure model to assess competition among VCs—some of which specialize in a particular industry and others of which are generalists—and find that the incremental effect of additional same-type competitors increases as the number of same-type competitors increases. Furthermore, we find that the effects of generalist VCs on specialists are substantial, and larger than the effect of same-type competitors. Estimates from other industries typically show the incremental effects falling as the number of same-type competitors increases and the effects of same-type competitors as always being larger than the effects of different-type competitors. Consistent with the presence of network effects that soften competition, these patterns are more pronounced in markets that exhibit dense organizational networks among incumbent VCs. Markets with sparser incumbent networks, by contrast, exhibit competitive patterns that resemble those of other, non-networked industries.

Keywords Venture capital · Specialization · Product differentiation · Competition · Networks

✉ Michael J. Mazzeo
mazzeo@kellogg.northwestern.edu

Yael V. Hochberg
Hochberg@rice.edu

Ryan C. McDevitt
ryan.mcdevitt@duke.edu

1 Jones School of Business, Rice University, 6100 Main Street, MS-531, Houston, TX 77005, USA

2 Kellogg School of Management, Northwestern University, 2001 Sheridan Road, Evanston, IL 60208, USA

3 Fuqua School of Business, Duke University, 100 Fuqua Drive, Durham, NC 27708, USA

1 Introduction

Within the entrepreneurial ecosystem, venture capitalists (VCs) serve a vital economic function by identifying, funding, and nurturing promising entrepreneurs. Whether VCs provide capital and services on competitive terms, however, is much debated among practitioners and in the academic literature. This paper explores how differentiation among venture capitalists—in the form of their choices with regard to industry specialization—interacts with competition to affect market structure and outcomes in local VC markets.[1]

Entrepreneurs typically view VCs as offering differentiated value-added services in addition to their otherwise functionally-equivalent capital (Hsu (2004)). A VC might specialize because its principals hold sector-specific expertise that affords them advantages when selecting or managing ventures. On the other hand, an abundance of investment opportunities in a particular sector may attract several competing venture funds, which results in higher bids or valuations. In such a circumstance, a VC might find investing (and indeed, perhaps, specializing) in less-crowded sectors preferable. With each investment, the VC must weigh the benefits of reduced competition against the potential returns to specialization and the appeal of thick market sectors.

Empirical evidence with regard to VC competition is limited, in part because valuations and investment are arrived at through individual negotiations. Structural methods in industrial organization, however, permit analysis based on easily available data such as the number of operating firms in a market and their differentiation strategies. We follow the approach of Mazzeo (2002), where firms offer discrete heterogeneous product types: In our setting, a market's VC firms decide whether or not to specialize in investing in a particular industry segment. Estimates from the model measure the incremental effect of additional VCs on competition and explicitly compare the effects that specialists and generalists have within and across their types.

We assemble a dataset of U.S. VC funds and investments, in oligopoly markets, where coordination costs are lower and concerns about competition are likely more pronounced (Hochberg et al. (2010)). The results suggest that VC markets are competitive, but the incremental effect of additional same-type competitors *increases* as the number of same-type competitors increases. Furthermore, the effects of generalist investors on specialists are substantial, and larger than the effect of same-type competitors. This pattern differs starkly from other industries, which typically show the incremental effects falling as the number of same-type competitors increases and the effects of same-type competitors as always being larger than the effects of different-type competitors.

These unique findings are consistent with the presence of strong co-investment networks, which suggests that cooperative relationships in the VC industry may

[1] Our work is part of an emerging literature on specialization in the VC industry. Sorenson (2008) explores the tradeoff between specialization as an exploitation strategy and exploration outside a VC's area of expertise. Gompers et al. (2009) examine the relationship between specialization of individual human capital and VC success (without endogenizing the VC's specialization decision). Hochberg and Westerfield (2012) compare VC fund specialization and portfolio size.

soften the effects of competition. We find evidence that is consistent with this hypothesis by estimating our model separately for the subsamples of local markets with higher and lower VC network density.[2] Markets with higher network density exhibit the same patterns as the full sample, while markets with lower network density exhibit competitive patterns that are typical of other industries.

The remainder of the paper is organized as follows: Sect. 2 describes the structural model of market structure that is employed in our analysis. Section 3 describes the sample and data, and presents descriptive statistics on the structure of local VC markets. Section 4 presents and discusses the estimates from our structural model. Section 5 concludes.

2 A Model of Endogenous Market Structure in Venture Capital

To examine the effects of sector specialization and competition in VC markets, we employ the so-called "multiple-agent qualitative-response" model that is used in industrial organization to evaluate market competition (see Reiss (1996) for an overview of the empirical framework).[3] These models use observed data on firms' choices (e.g., operating in a market, specializing in a sector, etc.) and other market characteristics to estimate the parameters governing firms' unobservable profits.[4]

The logic behind a structural model of entry and specialization choices is that a VC firm's market presence indicates that the VC firm must expect to earn positive profits in that market. This "revealed preference" argument allows us to infer how much competition and specialization decisions affect expected profits, as the estimated likelihood of observing a given market configuration varies with the extent of competition in that market, all else equal. Crucially, as we will show below, our structural model of competition allows us to connect observed choices that have been made by VCs to the attractiveness of operating in the market based

[2] In the literature on VC networks, Sorenson and Stuart (2001) explore how ties among VCs affect geographic patterns of exchange. Hochberg et al. (2007) examine the relationship between a VC's network position and performance, while Hochberg et al. (2010) focus on the effects of networks on market entry and valuations paid to entrepreneurs. Hochberg et al. (2015) discuss various theories of network tie formation in VC, including the sharing of resources across VCs. We believe that ours is the first study to investigate differentiated competition and endogenous market structure in an industry that is networked in the way that the VC industry is.

[3] Two popular proxies used in the industrial organization literature for assessing competition are concentration indices, such as the Herfindahl, and own- and cross-price elasticities of demand. Both approaches suffer from shortcomings, and neither offers a definitive measure of competitiveness—particularly in markets with differentiated competitors. A theoretical basis for the use of the Herfindahl is a Cournot equilibrium with homogeneous firms, and thus it may not be well suited for assessing the extent of competition among differentiated competitors. While the cross-price elasticity of demand approach yields useful results for market structure simulations, it requires more detailed data than is commonly available and does not account for strategic interaction among firms in concentrated markets.

[4] The analytical framework derives from Bresnahan and Reiss (1991), who propose a simple yet flexible profit function that governs behavior in a symmetric equilibrium in market *m*. Bresnahan and Reiss (1991) assume that firms will participate in the market if they earn nonnegative profits. An ordered probit model is then used to estimate the parameters of their profit function. For additional development of the basic approach, see Berry (1992), Toivanen and Waterson (2005) and Seim (2006).

on these choices. That is, we can use data on just the number of VCs in a market to make inferences about the underlying attractiveness of operating even without detailed information on prices and costs.

The basic intuition that underlies such models is the following: If we abstract, for a moment, from decisions about sector specialization, consider a dataset with observations on the number of homogeneous firms across M markets, $N_1, \ldots, N_M$. Given N_i participants in market i, assume an operating firm in that market earns

$$\pi(N_i) = V(N_i, x_i, \theta),$$

where $V(.)$ represents the firms' variable profits, the x_i are market characteristics such as population, and θ is a vector of estimable parameters that govern how competition influences profits.

The fundamental modeling assumption is that, if we observe N^* firms in the data, then all N^* at least break even, such that

$$V(N^*, x, \theta) \geq 0.$$

Further, any additional market participant would not break even (or else the firm would have chosen to operate and earn positive profits), such that

$$V(N^* + 1, x, \theta) < 0.$$

These conditions, coupled with an assumption on an unobserved error term ε that affects profits, provide a means by which we can estimate θ simply from data on N and x:

$$Prob(V(N^*, x, \theta) \geq 0|x) - Prob(V(N^* + 1, x, \theta) > 0|x) = \Phi(V(N^*, x, \theta)|x) - \Phi(V(N^* + 1, x, \theta)|x),$$

with the assumption that the error draws have an i.i.d. standard normal distribution. From here, it is straightforward to estimate θ using maximum likelihood techniques. Importantly, θ has the natural reduced-form interpretation of representing the impact of competition on profits: A one-unit increase in competition reduces profits by θ, as it reduces the likelihood that a firm reaches the break-even threshold.

To accommodate differentiation among competitors, we follow Mazzeo (2002) and employ a model that endogenizes product-type choice as well as the market-presence decision. We identify competitors as being one of three types of VCs depending on their specialization strategy (either "dominant sector specialist", "other (non-dominant) sector specialist", or "generalist") and specify a separate function for VCs of each type. This allows us to determine whether same-type competitors have a greater effect than different-type competitors. We include both the number and product types of competitors as arguments in a reduced-form "payoff" function that captures the attractiveness of operating for the VC. We treat all VCs within a given type as symmetric.[5]

[5] As such, a limitation of our approach is that we cannot specifically address the potential heterogeneous impact of particular competitors within type—for example, whether some generalist VCs have more of a competitive effect than others. Indeed, to the extent that within-type heterogeneity may exist for our defined specialization strategies, this may have an impact on the value of the estimated parameters (see

More generally, we can specify the "payoffs" of a firm of type τ in market m, where market m contains N_1 firms of type 1, N_2 firms of type 2, and N_3 firms of type 3[6]:

$$\pi_{\tau,m,N_1,N_2,N_3} = X_m\beta_\tau + g(\theta_\tau; N_1, N_2, N_3) + \varepsilon_{\tau m} \tag{1}$$

The first term represents market demand characteristics that affect the attractiveness of operating the VC (note that the effect of X_m is allowed to vary by type). The $g(\theta_\tau; N_1, N_2, N_3)$ portion captures the effects of competitors, with N_1, N_2, and N_3 representing the number of competing firms of each type. Parameters in the $g(\theta_\tau; N_1, N_2, N_3)$ function can distinguish between the effects of same-type firms and the competitive effects of firms of each of the different types. The set of θ parameters can also be specified to capture the incremental effects of additional firms of each type. Note that the parameter vector θ varies across types; this allows the competitive effects to potentially differ by type.

The estimates that are reported in section III reflect the following specification of the competitive-effect dummy variables[7]:

$$\begin{aligned} g_D &= \theta_{DD1} * \text{ presence of first dominant sector specialist competitor} \\ &+ \theta_{DD2} * \text{ number of additional dominant sector specialist competitors} \\ &+ \theta_{DO1} * \text{ presence of other sector specialist competitor} \\ &+ \theta_{DO2} * \text{ number of additional other sector specialist competitors} \\ &+ \theta_{DG1} * \text{ presence of first generalist competitor} \\ &+ \theta_{DG2} * \text{ number of additional generalist competitors} \end{aligned} \tag{2}$$

$$\begin{aligned} g_O &= \theta_{OO1} * \text{ presence of first other sector specialist competitor} \\ &+ \theta_{OO2} * \text{ number of additional other sector specialist competitors} \\ &+ \theta_{OD1} * \text{ presence of first dominant sector specialist competitor} \\ &+ \theta_{OD2} * \text{ number of additional dominant sector specialist competitors} \\ &+ \theta_{OG1} * \text{ presence of first generalist competitor} \\ &+ \theta_{OG2} * \text{ number of additional generalist competitors} \end{aligned} \tag{3}$$

Footnote 5 continued
the discussion of this in the results section below). While we will not be able to say whether other types of heterogeneity may or may not have a similar effect, we can make statements with regard to whether this chosen measure of differentiation does matter.

[6] This specification function was chosen primarily to make the estimation tractable. Following Berry (1992) and Bresnahan and Reiss (1991), it can be interpreted as the log of a demand (market size) term multiplied by a variable profits term that depends on the number (and product types, in this case) of market competitors. There are no firm-specific factors included. The error term represents unobserved payoffs from operating as a particular type in a given market. It is assumed to be additively separable, independent of the observables (including the number of market competitors), and identical for each VC firm of the same type in a given market.

[7] The goal is to make the specification of the competitive effects as flexible as possible, while maintaining estimation feasibility. For example, in the cases where the data represent the "number" of competitors, we implicitly assume that the incremental effect of each additional competitor is the same. The specification also reflects the maximum number of VCs of each type, as discussed below.

$$
\begin{aligned}
g_G = {} & \theta_{GG1} * \text{ presence of first generalist competitor} \\
& + \theta_{GG2} * \text{ number of additional generalist competitors} \\
& + \theta_{OD1} * \text{ presence of first dominant sector specialist competitor} \\
& + \theta_{OD2} * \text{ number of additional dominant sector specialist competitors} \\
& + \theta_{GO1} * \text{ presence of first other sector specialist competitor} \\
& + \theta_{GO2} * \text{ number of additional other sector specialist competitors}
\end{aligned} \tag{4}
$$

We specify the unobservables, ε_{DOG}, to follow an independent standard trivariate normal distribution. As such, there is no implied correlation among the individual elements of (ε_D, ε_O, ε_G) within a given market, and the variance of the unobservables is the same for all types.

As outlined in Eqs. (2–4), the right hand side variables appear to be endogenous since they represent strategic decisions that have been made by competitors. To address this endogeneity issue, we need to make an assumption about the nature of the process that generates the observed market configuration of VCs. We begin by assuming that there are three possible types of VCs that could operate in a given market: dominant-sector specialist (D), other-sector specialist (O), or generalists (G).[8] If we abstract from differences among firms of the same type, firms that operate in market *m* earn $\pi_{\tau m}(N_1, N_2, N_3)$, where τ is the product type of the firm and the ordered triple (N_1, N_2, N_3) represents the number and product types of all of the competitors that also operate in market *m*.[9] Firms that do not operate earn zero.

We estimate the model with the assumption that the observed market outcome is arrived at as if potential market participants of each type were playing a Stackelberg game. In such a specification, players of the various types sequentially make irrevocable decisions before the next firm plays. As they make these decisions, firms anticipate that potential competitors of all types will subsequently make decisions once the earlier movers have committed to their choice.[10]

Conceptualizing competition using this game structure allows us to make inferences based on the observed set of VCs that operate in the market. A Nash

[8] Alternatively, the set up is equivalent to assuming that the VCs have inherent types and make operating decisions that are embodied by the companies in which they make investments. As such, the specialization choice would be made upfront when the VCs initially raise the fund. With this framing, the decision can be rationalized either about operating in the market or about product-type choice; either way, we can make the inferences as described below. Empirically, we are examining the realization of this choice each period.

[9] We implicitly assume that VCs that operate in multiple geographic markets make their sector specialization decisions on a market-by-market basis.

[10] The Stackelberg game has the attractive feature that the highest payoff types will have the largest presence in the resulting market configuration. A natural alternative is a simultaneous move game; however, it has been well established that such a game has multiple equilibria, which precludes straightforward econometric estimation (see Tamer (2003)). We proceed with the Stackelberg assumption, in part relying on the finding in Mazzeo (2002) that parameter estimates are very similar across various game formulations. A unique equilibrium to this game is only ensured if the competitive effects are restricted to be negative; an assumption that we do not impose due to the possibility of benefits from cooperation in the VC context, as described below.

Equilibrium can be represented by an ordered triple (D, O, G) for which the following inequalities are satisfied:

$$\begin{array}{ll} \pi_D(D-1,O,G) > 0 & \pi_D(D,O,G) < 0 \\ \pi_O(D,O-1,G) > 0 & \pi_O(D,O,G) < 0 \\ \pi_G(D,O,G-1) > 0 & \pi_G(D,O,G) < 0 \end{array} \tag{5}$$

and

$$\begin{array}{c} \pi_D(D-1,O,G) > \pi_O(D-1,O,G) \\ \pi_D(D-1,O,G) > \pi_G(D-1,O,G) \\ \pi_O(D,O-1,G) > \pi_D(D,O-1,G) \\ \pi_O(D,O-1,G) > \pi_G(D,O-1,G) \\ \pi_G(D,O,G-1) > \pi_D(D,O,G-1) \\ \pi_G(D,O,G-1) > \pi_O(D,O,G-1). \end{array} \tag{6}$$

The inequalities in Eq. (5) formalize the assumption that firms that operate in the market do so because it is attractive to do so; any additional firms (of any of the three types) would not find it attractive. The inequalities in (6) represent the assumption that no firm that is currently operating in the market would do better as a firm of a different type. In other words, all the operating firms have made the appropriate decisions, given the specialization of their competitors.

The model estimates all the inequalities simultaneously, which endogenizes the right-hand-side dummy variables that represent the presence of competition. Note that the endogeneity problem that is related to the specialization choice variables is taken care of by the game theoretic assumptions that are embedded in the equilibrium model; in effect, the model allows us to estimate several equations simultaneously, with the variables on the right-side of one equation on the left-side of another. By contrast, a reduced-form estimation of the equations above would not have accounted for the confounding actions of optimizing agents, which would likely bias the results. By explicitly modeling the optimizing behavior, the resulting estimation does not suffer from these same concerns over endogeneity.

Under the specification described above, the inequalities that correspond to exactly one of the possible ordered-triple market structure outcomes are satisfied for every possible realization of (ε_D, ε_O, ε_G) based on the data for the market in question and values for the parameters. A predicted probability for each of the possible outcomes is calculated by integrating $f(\varepsilon_D, \varepsilon_O, \varepsilon_G)$ over the region of the $\{\varepsilon_D, \varepsilon_O, \varepsilon_G\}$ space that corresponds to that outcome. Maximum likelihood selects the parameters that maximize the probability of the observed market configurations across the dataset.

The likelihood function is:

$$L = \prod_{m=1}^{M} \text{Prob}\left[(D,O,G)_m^A\right] \tag{7}$$

where $(D, O, G)_m^A$ is the actual configuration of firms in market m; its probability is a function of the Stackelberg solution concept, the parameters, and the data for market m. For example, if $(D, O, G)_m^A = (1, 1, 1)$ for market m, the contribution to the likelihood function for market m is Prob[(1,1,1)].[11]

Before we leave our presentation of the econometric model, it is worth noting the assumptions that underlie our interpretation of the estimated θ parameters as the incremental effects of various competitors. In particular, without data on costs, we must assume that VCs share a common minimum efficient scale; otherwise, we would observe ever-larger VCs that would dominate markets rather than a positive correlation between a market's entrepreneurial activity and the number of VCs that are present. Data requirements and estimation tractability necessitate abstracting away from differences among VCs other than their specialization decisions. Though each VC brings its own idiosyncratic networks and skills to bear in a market where it operates, these unique features are more likely to determine which—not how many—VCs of each type will operate.[12]

Furthermore, there are almost certainly other types of differentiation that VCs exploit in market competition (for example, age or experience); our methodology is not able to evaluate multiple dimensions of differentiation simultaneously or test which may be most relevant. However, we are able to examine the extent to which this particular type of differentiation—based on specialization decisions—affects market outcomes. The importance of other types of differentiation will help in the interpretation of the competition parameters that we do estimate.

3 Sample and Data

The data for our empirical analysis come from Thomson Financial's Venture Economics database. Venture Economics began compiling data on venture capital investments in 1977, and has since backfilled the data to the early 1960s. Gompers and Lerner (1999) investigate the completeness of the Venture Economics database and conclude that it covers more than 90 % of all venture investments.[13] Our sample, which is also employed in Hochberg et al. (2007), covers investments that were made over the period 1975–2008.

[11] Analytically computing the probability of each outcome is exceedingly complex in the case of three product types. As a result, a frequency simulation approach is used, whereby random draws are taken from the assumed error distribution. For each random draw, a unique simulated product-type configuration is generated for each market based on the data for that market, the parameters, and the value of the random draw. Parameters are chosen that maximize the number of times that the simulated configuration equals the observed configuration. See Mazzeo (2002) for additional details.

[12] Some progress has been made—see Ciliberto and Tamer (2009)—in more straightforward industries, such as airlines, where the total number of firms that are able to operate in a market is quite small.

[13] Most VC funds are structured as closed-end, often ten-year, limited partnerships. They are not usually traded, nor do they disclose fund valuations. The typical fund spends its first three or so years selecting companies to invest in, and then nurtures them over the next few years. In the second half of a fund's life, successful portfolio companies are exited via IPOs or trade sales to other companies, which generates capital inflows that are distributed to the fund's investors. At the end of the fund's life, any remaining portfolio holdings are sold or liquidated, and the proceeds are distributed to investors.

We concentrate solely on the investment activity of U.S.-based VC funds, and exclude investments by "angels" and buyout firms. While VC funds have a limited (usually 10-year) life, the VC firms that control the funds have no predetermined lifespan. Success in a first-time fund often enables the VC firm to raise a follow-on fund (Kaplan and Schoar (2005)), which results in a sequence of funds raised a few years apart. Startup companies that are trying to raise capital generally seek this capital from a VC firm, rather than from a specific fund within that VC firm; and the experience, contacts, and human capital acquired while running one fund typically carries over to the next fund. As market presence and 'type' decisions are related to the demand for capital and services from entrepreneurs, we focus here on specialization at the firm level and refer to the VC firm as a VC.

When analyzing VC competition, the geographic match between venture capitalists and startup companies that are seeking capital is critical. The nature of these relationships—including research, due diligence, establishing personal contacts, and monitoring of portfolio companies—makes venture capital a decidedly local industry.[14] As a result, we explore competition at the local geographic market level, which we define as the Metropolitan Statistical Area (MSA) in which the VC invests in a startup. Two or more VCs that have made investments in a particular MSA are assumed to be competitors, and we proxy for the industry sector specialization of VCs based on their portfolio of startup companies in that MSA.[15] The relevant units of observation are the MSA-year (for markets) and the VC-market-year (for individual investing VCs).

Table 1 summarizes our data with regard to market participation at the MSA-year level. The frequency column indicates the number of market-year observations that contain the corresponding number of operating VCs. Note that there is considerable variety in the aggregate measure of competition across VC markets. While the familiar notion of a populated VC market such as Silicon Valley or Route 128 is represented at one end of the spectrum, the majority of geographic markets have relatively few operating VCs. Concerns about competition in markets with smaller numbers of VCs are likely to be larger, as smaller VC markets appear to allow for a higher likelihood of strategic coordination amongst participants (Hochberg et al. (2010)).

In our analysis, we focus on a particularly important dimension of differentiation among VCs: industry sector specialization. Some VCs choose to specialize in a particular industry, while others act as generalists and invest across industries. For example, Sequoia Capital XI—a large VC fund that was raised in 2003—successfully invested in both shoe stores and network security startup companies (Zappos.com and Sourcefire). The same fund also invested in fabless semiconductors (Xceive), network control technology (ConSentry), airline IT and services (ITA), and social networking websites (LinkedIn). In contrast, Longitude Venture Partners—a smaller VC fund that was raised in 2008—focuses on

[14] Furthermore, Sorenson and Stuart (2001) show that VCs tend to invest locally, which provides additional support in favor of segmenting markets geographically.

[15] While entrepreneurs may consider the portfolio of past startup investments that a VC has made in other markets as well when considering the relevant expertise and specialization area of a VC, the local market portfolio of the VC is likely to be a prominent consideration.

Table 1 The number of VCs that operate in local markets

Number of VCs	Freq.	Percent	Cumulative
0	5966	53.8	53.8
1	984	8.9	62.7
2	594	5.4	68.1
3	337	3.0	71.1
4	274	2.5	73.6
5	243	2.2	75.8
6	180	1.6	77.4
7	142	1.3	78.7
8	137	1.2	79.9
9	110	1.0	80.9
10	111	1.0	81.9
11	98	0.9	82.8
12	81	0.7	83.5
13	54	0.5	84.0
14	77	0.7	84.7
15	44	0.4	85.1
16	59	0.5	85.6
17	66	0.6	86.2
18	66	0.6	86.8
19	47	0.4	87.2
20	50	0.5	87.7
21+	1364	12.3	100.0
Total	11,084	100.0	100.0

The table presents a histogram for the number of VCs operating in the local geographic market in a given year. Markets are defined based on Metropolitan Statistical Area (MSA)/Consolidated MSA (CMSA). We have 326 markets and 34 years for a total of 11,084 market-years

biotechnology investments, and its portfolio consists primarily of drug development companies.[16]

We define a VC as being specialized in a particular sector in year *t* if it has made greater than 90 % of its market-level investments in that sector over the previous 5-year period and has made more than one investment during that time period.[17] Any VC that makes fewer than 90 % of its investments in one particular sector in the market over the preceding 5-year period is considered to be a generalist. In what follows, all of our analyses are robust to changes in this threshold from 90 to 60 %.

[16] VCs also differ by geographic focus, with some that invest nationally and others that focus investment activity in a particular geographic region or regions. While geographic specialization may also represent a meaningful source of differentiation, we focus here on industry scope differentiation, which is of primary importance in the eyes of entrepreneurs that seek VC funding. As our empirical methods are not rich enough to simultaneously consider differentiation along both dimensions of specialization, we leave an exploration of the competitive effects of geographic specialization to future research.

[17] Because there are very few individual investments that are made by any single VC in a given year, it is a common convention in the VC literature to calculate proxies for characteristics such as specialization, network centrality, etc., by using some years of trailing data. Thus, specialization in year t will commonly be calculated as the industry HHI based on all investments made by the VC in years t-4 to t.

Table 2 VC sector specialization

Industry sector	Freq.	Percent	Cumulative
Biotechnology	523	7.0	7.0
Communications and media	968	13.0	20.0
Computer-related	1747	23.4	43.4
Medical	1119	15.0	58.3
Non-high technology	1778	23.8	82.1
Semiconductors	432	5.8	87.9
Generalist	905	12.1	100
Total	7472	100.0	100.0

The table presents a histogram for the number of VCs operating in the local geographic market-year as specialists in each of six industry sectors or as generalists. Markets are defined based on Metropolitan Statistical Area (MSA). Industry sectors are defined by the six Venture Economics industry categories: Biotechnology; communications and media; computer related; medical/health/life science; semiconductors/other electronics; and non-high-technology. We define a VC as a specialist in a given industry sector for market m in year t if the VC has made over 90 % of its investments in that sector in market m over the preceding 5-year period. We restrict our analysis to VCs that operate in oligopoly markets where there are five or fewer operating dominant sector specialists, five or fewer non-dominant sector specialists, and three or fewer generalists

The industry sectors that we consider in our analysis are the six broad industry sectors that are defined by Venture Economics: biotechnology, communications and media, computer-related, medical, non-high technology, and semiconductors.[18] We provide a frequency table for the sectors of VC-level specialization in Table 2. Each of the six industry categories have some VCs that specialize only in that sector, with a low of six percent in semiconductors; approximately 12 % of the VCs in our data are classified as generalists.

As our structural model can accommodate at most three distinct 'types' of competitors before estimation becomes infeasible, we focus on specialists in the dominant industry sector for the market, the pool of specialists in non-dominant industry sectors for the market, and generalists. We define the dominant industry sector in each geographic market in each year as the sector among the six VC industry sectors (as defined by Venture Economics) that has the greatest number of specialists in that geographic market. For example, if three VCs in a market specialize in biotechnology startup companies and two specialize in semiconductor startups, we will define biotechnology as that market's dominant sector. VCs in that market that specialize in a sector other than the dominant sector are then categorized as non-dominant sector specialists.[19]

[18] As a robustness check, we collapsed the six Venture Economics categories into three broader categories: "Health" comprises biotechnology and medical; "Technology" comprises computer-related and semiconductors; and "Media" comprises communications and media. When we re-ran the structural model with a definition of VC specialization that is based on investments in these three broader categories, our empirical results were qualitatively similar to the results that are reported in the following section.

[19] We define VCs that have made only one investment over the previous five years—and are thus vacuously specialized—as fringe VCs.

Explicitly allowing for dominant and non-dominant sector specialists allows us to address two important features of these markets: First, it allows us to circumvent the obvious concern that specialists are further differentiated within-type: A specialist in the biotechnology industry should not be considered the same 'type' as a specialist in semiconductors, yet we are explicitly interested in examining the competitive effects of one biotechnology specialist on another, and the effect of a generalist on the biotechnology specialist and vice versa. Defining a dominant market-level specialization sector provides the ability to examine the within-type competitive effects for a single sector of specialization: that which is most prevalent in the market.

If, however, we were to ignore specialists in sectors outside the dominant sector of a market, we might then mis-estimate the competitive effects of the generalist investor that is likely affected not only by the presence of dominant sector specialists, but also by any other specialist investors in the market. Pooling non-dominant sector specialists allows us to accommodate their cross-effect on generalists, even if it does not allow us to examine precisely their within-type competitive effects. We thus identify within-type competitive effects of specialist investors from the dominant sector specialists and generalists, and view the non-dominant sector specialists as a form of control variable.

We restrict our analysis to geographic markets in which the set of existing VCs that we identify are most likely to be oligopolistic competitors (i.e., the set of VCs possibly going after the same deals) and exclude markets with a very large number of VCs that are typically considered to be quite competitive.[20] These geographic areas may also contain many distinct submarkets that we could not identify separately from our aggregated data. As a consequence, we do not consider the very largest VC markets; even though these markets do represent a substantial share of overall VC activity, they are not markets where we would expect to observe interaction between sector specialization and competition.[21]

Instead, we focus on those markets with five or fewer specialists in the market's dominant sector, five or fewer specialists in the market's non-dominant sector, and three or fewer generalists. Given this sample restriction, we move from 11,084 market-years to 9619 across 326 distinct markets, which allows us better to match

[20] Bresnahan and Reiss (1991) find that the additional competitive effect of market participants dies out once there are four or five (homogeneous) firms in the industry. This finding (together with the computational issue described below) explains why papers in this literature (e.g., Mazzeo 2002; Seim 2006) focus on smaller markets.

[21] For computational reasons, markets with a very large number of participants are prohibitively difficult to estimate, since the dimensionality of the probability space for the likelihood in Eq. 7 increases very quickly as the number of market participants increases. To help alleviate concerns regarding dropping these largest VC markets, we performed a series of ordered probit estimations, whose dependent variables were the number of VCs of each type. These estimated parameters in these ordered probits were similar when we included the markets that are dropped in the structural model and when we did not, which suggests that the underlying competitive behavior that we estimate is similar in the large markets that we are forced to drop.

Table 3 Summary statistics

	Mean	SD	Min	Max
# Dominant sector VCs	0.395	1.002	0	5
# Non-dominant sector VCs	0.287	0.817	0	5
# Generalist VCs	0.094	0.392	0	3
# fringe VCs	1.269	2.858	0	30
Market size	28,198.9	113,318.3	0	2,061,438
Population	866,327.8	2,269,706	43,796	1.86E07
Per capita income	17,151	8983.2	3198	78,842.85
Network density	0.132	0.308	0	1
Market fixed effect	0.583	2.345	−21.831	66.803

The unit of observation in this table is a market-year. We define a market as a metropolitan statistical area (MSA). Industry sectors are defined by the six Venture Economics industry categories: Biotechnology; communications and media; computer related; medical/health/life science; semiconductors/other electronics; and non-high-technology. We define a VC as a specialist in a given industry sector for market *m* in year *t* if the VC has made over 90 % of its investments in that sector in market *m* over the preceding 5-year period. We define the dominant industry sector for a given market-year as the sector in which the majority of operating VCs is specialized. A VC is defined as a generalist if it is not specialized in an industry sector. VCs with only one investment during the time period over which specialization is defined are considered to be fringe firms. Market size is defined as the dollar amount of VC deals done in the market in the preceding year. MSA population and per capita income data come from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). Network density is defined as the proportion of all logically possible ties among operating VC firms that are present in the market, and is calculated from the undirected network resulting from VC firm co-investment in startup companies over the preceding 5 year period. Market fixed effect is the fixed effect from a regression of VCs on several controls described in Section III. There are 9,619 distinct market-years, involving 326 distinct MSAs. We restrict our analysis to VC firms that operate in oligopoly markets where there are five or fewer operating dominant sector specialists, five or fewer non-dominant sector specialists, and three or fewer generalists

the assumptions of the econometric model and its underlying game-theoretic model of competition with the processes that determine the observations in our data set.[22]

In addition to the number and type of competitors in the market, our model includes market-level variables that capture the effects of market-level characteristics for each type of VC firm. As a measure of market size, we use the natural logarithm of the dollar amount of VC investments in the market over the preceding 5-year period. To capture possible economic activity, we use the natural logarithm of the MSA's population and of per-capita income; both are obtained from the Bureau of Economic Analysis.

To allow us to distinguish between markets where cooperative ties between competitors are strong versus weak, we further compute the network density for each geographic market. The network density is measured as the proportion of all

[22] Because of the sample restriction, our data do not represent a balanced panel in the sense that a market may enter and exit the panel based on the number of VCs that are present in a given year. In other words, 326 markets have at least one year that satisfies the sample restriction.

logically possible ties among operating VCs that are present in the market based on actual VC co-investments in startup companies over the preceding 5-year period.[23]

Summary statistics for our data appear in Table 3. The number of dominant sector specialist VCs ranges from zero to five, with a mean of 0.395 per market-year in our sample and slightly fewer VCs that specialize in other, non-dominant sectors in each market-year. There are approximately 1.3 fringe firms that operate on average in each market-year. The average market has a density of network ties among VCs of 0.132, with network density varying from zero to 1.

To capture unobservable market-level features that might make an area well suited for VC activity, we compute a market fixed effect that is estimated from an OLS regression of the number of VCs in a market on our other controls; this variable ranges from −21.8 (fewer VCs than expected given other observable characteristics) to 66.8 (more VCs than expected). Although ideally we would include a market fixed effect directly into our model, doing so would introduce an additional 3×326 parameters to estimate (one for each market and specialization type), making estimation intractable. The incorporation of a single continuous variable from a reduced-form regression into the structural model introduces only 3×1 parameters while still capturing much of the unobserved market forces that would influence VC choices; this is a worthwhile compromise given the computational gains.

To allow for identification of our structural model, one industry sector cannot be defined as the dominant sector; this enables us to observe configurations such as (0,1,1), (0,2,0), etc., which are required for identification of the competitive effects.[24] Given its composition, we chose the "non-high-technology" sector to be this omitted category. Based on these definitions, Table 4 presents a summary of the observed market configurations in our sample. The most common configuration of the market has zero dominant sector specialists, zero other sector specialists, and zero generalists.[25] The second most common configuration has one dominant market specialist and zero competitors of either other type (1,0,0). The configuration with the maximum allowable number of each of the three types, (5,5,3), makes up <0.1 % of our sample.

[23] Following Hochberg et al. (2007, 2010), we use social network analysis to measure the extent to which VCs are interconnected. Networks are represented as matrices, and are calculated for each year t based on the investments made by the VCs in a given market during the preceding five-year period. Cells reflect whether two VCs co-syndicated at least one deal during the formation period. A natural measure of how interconnected incumbents are is "density," which is defined as the proportion of all logically possible ties that are present in a market. For example, the maximum number of ties among three incumbents is three. If only two incumbents are connected to each other, the density is 1/3 (one tie out of the three possible). With n incumbents, there are at most ½n (n − 1) ties. Let $P_{ijm} = 1$ if VCs i and j have made a co-investment market m, and zero otherwise. Then market m's density equals $\Sigma_j \Sigma_i P_{ijm}/(n (n - 1))$.

[24] Recall that this market-level ordered triple will be the dependent variable of our econometric model; the resulting estimated parameters will define the attractiveness of operating as each VC type, given the specification described above.

[25] It is important to include these (0,0,0) markets in the empirical analysis, even though there are no competing VCs present. Markets with zero operating VCs help to identify the level of economic activity that is necessary to support a single VC in the market, which is critical for ultimately estimating the competitive effects. Without including these markets, we must make assumptions about initial market presence and estimate a conditional likelihood function instead (see Mazzeo 2002).

Table 4 Observed Market Configurations

# Dominant sector specialists	# Non-dominant specialists	# Generalists 0		1		2		3	
0	0	7,219	75.05 %	92	0.96 %	11	0.11 %	0	0.00 %
	1	316	3.29 %	27	0.28 %	5	0.05 %	1	0.01 %
	2	126	1.31 %	1	0.01 %	4	0.04 %	1	0.01 %
	3	38	0.40 %	6	0.06 %	3	0.03 %	0	0.00 %
	4	7	0.07 %	1	0.01 %	1	0.01 %	0	0.00 %
	5	10	0.10 %	0	0.00 %	0	0.00 %	0	0.00 %
1	0	412	4.28 %	32	0.33 %	13	0.14 %	6	0.06 %
	1	116	1.21 %	33	0.34 %	12	0.12 %	0	0.00 %
	2	47	0.49 %	16	0.17 %	5	0.05 %	0	0.00 %
	3	21	0.22 %	7	0.07 %	3	0.03 %	2	0.02 %
	4	7	0.07 %	3	0.03 %	1	0.01 %	2	0.02 %
	5	2	0.02 %	4	0.04 %	2	0.02 %	0	0.00 %
2	0	141	1.47 %	20	0.21 %	6	0.06 %	3	0.03 %
	1	77	0.80 %	23	0.24 %	9	0.09 %	0	0.00 %
	2	50	0.52 %	11	0.11 %	6	0.06 %	7	0.07 %
	3	17	0.18 %	14	0.15 %	3	0.03 %	3	0.03 %
	4	7	0.07 %	4	0.04 %	3	0.03 %	0	0.00 %
	5	3	0.03 %	1	0.01 %	0	0.00 %	0	0.00 %
3	0	76	0.79 %	20	0.21 %	1	0.01 %	6	0.06 %
	1	31	0.32 %	12	0.12 %	4	0.04 %	3	0.03 %
	2	17	0.18 %	16	0.17 %	4	0.04 %	0	0.00 %
	3	25	0.26 %	13	0.14 %	3	0.03 %	4	0.04 %
	4	11	0.11 %	4	0.04 %	5	0.05 %	4	0.04 %
	5	5	0.05 %	7	0.07 %	2	0.02 %	1	0.01 %
4	0	66	0.69 %	4	0.04 %	1	0.01 %	0	0.00 %
	1	27	0.28 %	10	0.10 %	7	0.07 %	1	0.01 %
	2	9	0.09 %	8	0.08 %	4	0.04 %	2	0.02 %
	3	12	0.12 %	12	0.12 %	6	0.06 %	0	0.00 %
	4	5	0.05 %	2	0.02 %	3	0.03 %	0	0.00 %
	5	5	0.05 %	3	0.03 %	2	0.02 %	3	0.03 %
5	0	38	0.40 %	4	0.04 %	0	0.00 %	1	0.01 %
	1	8	0.08 %	5	0.05 %	2	0.02 %	0	0.00 %
	2	9	0.09 %	4	0.04 %	1	0.01 %	3	0.03 %
	3	7	0.07 %	1	0.01 %	1	0.01 %	3	0.03 %
	4	8	0.08 %	8	0.08 %	3	0.03 %	4	0.04 %
	5	6	0.06 %	6	0.06 %	5	0.05 %	3	0.03 %

The table presents the number (and %) of markets in the sample that have each configuration of *(# dominant sector specialists, # non-dominant sector specialists, # generalists,)*. We define a market as a Metropolitan Statistical Area (MSA). Industry sectors are defined by the six Venture Economics industry categories. We define generalist and specialist VCs as in Table III. There are 9619 distinct market-years that involve 326 distinct MSAs. We restrict our analysis to VC firms that operate in oligopoly markets where there are five or fewer operating dominant sector specialists, five or fewer non-dominant sector specialists, and three or fewer generalists

4 Empirical Results

Table 5 presents the maximum likelihood estimates from our three-type endogenous market structure model for venture capitalist specialization. The parameter estimates allow us to compare the relative attractiveness of operating as each of the various types, and to check whether the operating threshold is met, under specific market conditions and in different competitive situations.

To start, the estimated constants reflect the baseline attractiveness of each specialization strategy absent competition and disregarding the values for all of the X-variables (all θ and β parameters also multiplied by zero). In this scenario, operating as an other-sector specialist (1.229) would be relatively more attractive

Table 5 Estimates of structural model

	θ	Std. Err.		β	Std. Err.
Competitive effects			Explanatory variables		
First dom on dom	−0.803	0.0245	*Dominant specialist sector*		
Second dom on dom	−2.715	0.0236	Intercept	0.117	0.0475
Each add. dom on dom	−1.376	0.0332	*ln* market size	1.46	0.0074
			ln population	−0.806	0.0069
First other on dom	−3.247	0.0193	*ln* Per capita income	−0.14	0.0133
Each add. other on dom	−4.491	0.034	Market fixed effect	−0.168	0.0045
First gen on dom	−6.037	0.0447			
Each add gen on dom	−0.115	0.0427	*Other specialist sectors*		
			Intercept	1.229	0.1267
First other on other	−0.802	0.0283	*ln* market size	*0.406*	0.1185
Second other on other	−7.366	0.0528	*ln* population	*−0.23*	0.0079
Each add. other on other	−4.304	44.478	*ln* per capita Income	*−0.235*	0.017
First dom on other	0.800	0.0576	Market fixed effect	0.274	0.0045
Each add. dom on other	−1.563	0.0236	*Generalists*		
First gen on other	−1.821	0.1253	Intercept	0.0853	0.0556
Each add. other on other	−0.181	0.135	*ln* market size	0.199	0.0134
			ln population	−0.232	0.0116
First gen on gen	−0.839	0.0401	*ln* per capita income	−0.123	0.021
Each add. gen on gen	−1.496	0.0965	Market fixed Effect	0.851	0.0073
First dom on gen	−0.994	0.055			
Each add dom on gen	−0.025	0.0357			
First other on gen	−3.312	0.0737			
Each add other on gen	−1.145	41.709			

The table presents the estimates from our structural model. Variables are as defined in Table III. We define a market as a Metropolitan Statistical Area (MSA). Industry sectors are defined by the six Venture Economics industry categories. We define generalist and specialist VC firms as in Table III. There are 9619 distinct market-years, involving 326 distinct MSAs. We restrict our analysis to oligopoly markets where there are five or fewer operating dominant sector specialists, five or fewer non-dominant sector specialists, and three or fewer generalists than operating as a dominant-sector specialist or as a generalist, though each type would find it attractive to operate in isolation.

The estimated coefficients on the *X*-variables for market size are broadly positive, reflecting that more VC firms of each type are likely to operate when these market size proxies are positive. Differences in the estimated β parameters across types reflect how these various measures might stimulate one type of VC firm more than another. Dominant-sector specialists, for example, do relatively better with greater investment volume (1.5 versus 0.4 and 0.2, respectively).

Note also that the coefficients on population and income are estimated to be negative for all types. Although seemingly counterintuitive, the inclusion of both a market size and a fixed effect parameter—which themselves are mostly positive—captures much of the variation that studies of other industries, such as motels, would usually ascribe to coarser measures of market potential such as population and income. In this case, with the inclusion of the controls for market size (i.e., investment volume) and market-level unobservables, a larger population and income correlate negatively with VC presence, perhaps because they are associated with higher operating costs (e.g., rents will be higher, which, all else equal, makes startups less viable).

The left-hand columns of Table 5 present the parameters (θ_T) that capture the amount by which the presence of particular competitors reduces the attractiveness of operating for each specialization type. For example, the estimated θ_{DD1} equals −0.803; therefore, we compute the attractiveness for a dominant sector VC that operates in a baseline market where the only competition is from another dominant sector VC as (0.117–0.803) = −0.686. To place this competitive effect within the context of our model, a dominant sector specialist would need log market size to increase by about half to offset the impact of the first same-type competitor present in the market, given our estimated market-size parameter of 1.46. Within-type effects for the first competitor appear to be similar across each type, at around −0.8.

When we look more closely at the set of estimated θ parameters, some interesting patterns emerge. To start, the incremental effect of additional same-type competitors *increases* as the number of same-type competitors increases for dominant-sector specialists and generalists. For example, the own-type effect of the second dominant specialist (−2.715) is greater than the first (−0.6803), as is the effect of each additional same-type competitor (−1.376). This finding contrasts with the findings in other industries (including telecommunications, lodging, banking, and healthcare) in which additional competitors of the same type have a less negative effect than the first same-type competitor. The same pattern exists within the other two defined VC types as well.

The remaining θ parameters represent the cross-type effects, which measure how VC firms of one type affect the other-type VC firms. In all cases, the effects of generalists on sector specialists (either dominant sector or other sector specialists) are quite substantial. Indeed, we can measure the effect of differentiation by comparing the estimated θ-parameters; for example, the first generalist competitor has a negative effect on a dominant sector specialist (−6.037), whereas the first dominant sector specialist slightly harms a generalist (−0.994). This comparison illustrates the crucial competitive role played by generalist VCs: if the dominant sector specialist's competitor in the previous example were a generalist instead, baseline attractiveness would be much worse: 0.117–6.037 = −5.92.

This finding is at odds with estimates of competitive effects in other industries; Table 6 presents findings in the literature from four such industries.[26] The motel industry estimates are for two product categories: high and low quality motels. The telecom industry estimates examine competition among "competitive local exchange carriers" (CLECs) that are focused on residential versus business segments. The healthcare industry estimates compare national health maintenance organizations (HMOs) and those with local footprints. Finally, the retail bank industry estimates distinguish multi-market banks, single market banks, and thrifts. The results consistently demonstrate same-type competition is more intense than competition from any other type and that the first competitor of each type has a greater effect than do additional same-type competitors.

One possible explanation for the contrast in the competitive effects that are estimated for the VC industry is unobserved within-type heterogeneity. As described above, our empirical model assumes that competitors within product types are the same. If there is substantial within-type heterogeneity, we would expect that the second competitor would try to be as distinct as possible from the first, notwithstanding the fact that they are of the same type with respect to sector specialization. This concern, however, is common to many of the industries that have been analyzed using Mazzeo-type models. Given the broad industry definitions that are used by providers of VC data, it is difficult for us to formally confirm or rule out this possibility, though it is reasonable to expect within-type heterogeneity given the idiosyncratic skills and relationships that are possessed by VCs.[27]

Estimates that suggest a positive impact of competitors on market attractiveness may be explained by the cooperative nature of VC networks, which is consistent with the presence of strong network ties in the VC industry. It is quite common for entrepreneurial ventures to be funded by multiple VCs, and the VC industry exhibits strong networks of co-investment and interaction amongst its participants at both the organizational (VC firm) and the personal (individual partner) level. These networks serve as a conduit for both the distribution and combination of resources and information across VCs (Bygrave (1988), Lerner (1994), Hochberg et al. (2007)).

Strong inter-VC ties offer the possibility that operating VCs within a market might have symbiotic relationships that partially offset any competitive effect if, for example, stronger network ties for a VC are associated with better performance and survival of their startup companies. This interpretation could help to explain our

[26] Motel industry estimates are obtained from Mazzeo (2002). Telecom industry estimates are for CLECs and are obtained from Greenstein and Mazzeo (2006). Health maintenance organization (HMO) industry estimates are obtained from Dranove et al. (2003). Retail depository institution estimates are obtained from Cohen and Mazzeo (2007).

[27] Agglomeration economies – either among VCs or the startup companies in which they invest—are an additional possibility that could generate the unique pattern of estimated coefficients. Indeed, other authors have found evidence of such agglomeration economies in this context (Florida and Kenney (1988); Saxenian (1994), and Chen et al. (2010)). We are hopeful that the market-level fixed effect that we estimate from the reduced form and include in the structural model would control for these effects; however, to the extent that it does not completely, this may be an alternative explanation.

Table 6 Model estimates in other industry settings

Industry	Motels		Telecom (CLECs)		Healthcare (HMOs)		Retail banks	
Product types	θ	Std. Err.	θ	Std. Err.	θ	Std. Err.	θ	Std. Err.
Effect on the presence of type 1 firms								
Of 1st type 1 firm	−1.7744	0.9229	−1.1903	0.0567	−1.07	0.1	−1.097	0.0646
Of 2nd type 1 firm	−0.6497	0.0927	−0.4834	0.0585	−0.68	0.07	−0.8193	0.0387
Of additional type 1 firm	–	–	–	–	−0.57	0.05	−0.7452	0.0195
Of 1st type 2 firm	−0.8552	0.9449	−0.4244	0.0745	–	–	−0.5453	0.1037
Of 2nd type 2 firm	–	–	−7.06E − 06	0.0003	–	–	–	–
Of additional type 2 firm	−0.1247	0.0982	−5.85E − 06	0.0003	−8.80E − 08	2.70E − 05	−0.1103	0.0513
Of 1st type 3 firm	–	–	–	–	–	–	−0.0329	0.1345
Of additional type 3 firm	–	–	–	–	–	–	−0.2745	0.092
Effect on the presence of type 2 firms								
Of 1st type 2 firm	−2.027	0.982	−1.36	0.0636	−1.05	0.11	−0.9291	0.0357
Of 2nd type 2 firm	−0.6841	0.0627	−0.5204	0.0567	−0.61	0.06	−0.7228	0.0375
Of additional type 2 firm	–	–	–	–	−0.46	0.04	−0.552	0.0375
Of 1st type 1 firm	−1.2261	0.9314	−5.59E − 05	0.0018	–	–	–	0.1706
Of 2nd type 1 firm	–	–	−9.29E − 06	0.0004	–	–	–	–
Of additional type 1 firm	−5.25E − 06	0.0006	−6.52E − 05	0.0005	−1.10E − 07	3.30E − 05	−0.1098	0.0513
Of 1st type 3 firm	–	–	–	–	–	–	−7.00E − 06	0.1665
Of additional type 3 firm	–	–	–	–	–	–	−0.1338	0.1596
Effect on the presence of type 3 firms								
Of 1st type 3 firm	–	–	–	–	–	–	−1.1889	0.0464
Of additional type 3 firm	–	–	–	–	–	–	−0.8918	0.0627
Of 1st type 1 firm	–	–	–	–	–	–	−0.0309	0.1768
Of additional type 1 firm	–	–	–	–	–	–	−0.0149	0.0691

Table 6 continued

Industry	Motels		Telecom (CLECs)		Healthcare (HMOs)		Retail banks	
Product types	θ	Std. Err.	θ	Std. Err.	θ	Std. Err.	θ	Std. Err.
Of 1st type 2 firm	–	–	–	–	–	–	−0.1214	0.1633
Of additional type 2 firm	–	–	–	–	–	–	−0.0004	0.1031

The table presents the estimates from Mazzeo-style structural models for other industry settings. The four industries are the motel industry, with differentiation between high and low quality product type; the telecom industry's competitive local exchange carriers (CLECs), with differentiation between residential- and business-focused product types; the healthcare industry's health maintenance organizations (HMOs), with differentiation between local and national footprint product types; and the retail bank industry, with differentiation between multi-market, single-market and thrift product types. Explanatory variables are included in all models but not reported for brevity unique result: The first VC "competitor" in a geographic market may have a positive networking impact that softens the typically negative competitive effect. Once a sufficient number of VCs are present in the market, however, the positive benefit of additional potential network partners grows smaller relative to the negative effect of additional competition for deals.

Markets vary in the extent of network ties among operating VCs and thus afford us a potential avenue to examine the hypothesis that the unique competitive patterns that we estimate for the VC industry derive from cooperative interaction among operating VCs that offsets (to some extent) the negative effects of competition. If cooperation and resource sharing among VCs provides a positive externality from the presence of an additional VC that dampens its competitive effects, we may expect that in markets in which VCs rarely form co-investment ties (low network density), competitive patterns would be closer to those observed in traditional industries. Similarly, if the patterns that were documented in the previous section result from the positive effects of these ties between VCs, they should be stronger in markets with high network density.

We evaluate this hypothesis by estimating our structural model separately for markets that exhibit high and low network density, and examining the resulting estimated effects of competition. Table 7 presents the estimates from our structural model, estimated separately for the subsample of markets with below- and above-mean network density, based on the market-level network density variable that was described in Sect. 2.[28,29] In the subsample of markets with below-mean density, we indeed observe a pattern of competitive effects that is much closer to that observed in other, non-networked industries. Critically, each additional dominant sector specialist competitor has a much smaller effect than either the first or second.

By contrast, the above-mean density subsample exhibits a similar pattern to the full sample estimates, wherein the competitive effect increases with each additional dominant sector specialist competitor. Thus, the estimates from the subsamples appear to be consistent with the notion that at least part of the difference between the patterns observed in the VC industry versus other, non-networked industries is related to the presence of strong networks among VCs.

Finally, the differences between VC markets and other industry markets appear to attenuate after one same-type competitor, as the effect of the second same type competitor is quite substantial among all of the sector specialization types. The

[28] As 55 % of the markets in our sample have a density of zero (i.e., no network ties amongst VCs), we use mean, rather than median, for our sample split. We obtain qualitatively similar results when segmenting in alternative fashions. We are treating the market-level network density variable as exogenous, though it might be argued that market-level network density is determined by individual VCs that decide whether to form cooperative relationships with other VCs in their markets. A model that endogenizes both sector specialization and network formation is beyond the scope of the econometric modeling in the industrial organization literature, though this is a potentially important issue that deserves its own, separate exploration.

[29] The log-likelihood for the estimation of below-mean markets is −14,378, which compares to a value of −110,021 when using the parameters at the maximum log-likelihood for above-mean markets. Similarly, the log-likelihood for the estimation of above-mean markets is −6,808, which compares to a value of −20,347 when using the parameters at the maximum log-likelihood for above-mean markets. As such, we consider the differences across market divisions to be statistically significant.

Table 7 Networked versus non-networked VC markets

	Below-mean network density markets		Above-mean network density markets	
	θ	Std. Err.	Θ	Std. Err.
Competitive effects				
First dom on dom	−2.004	0.0131	−1.239	0.055
Second dom on dom	−0.606	0.0174	−2.442	0.054
Each add. dom on dom	−0.821	0.0456	−3.617	0.0722
First other on dom	−2.215	0.0157	−2.683	0.0549
Each add. other on dom	−1.433	0.0274	−0.655	0.0462
First gen on dom	−1.265	0.0247	0.0002	0.0054
Each add gen on dom	−0.671	0.0573	−0.089	0.1235
First other on other	−2.39	0.0284	−5.148	0.0921
Second other on other	−2.851	0.0392	−0.797	0.0528
Each add. other on other	−0.921	0.0237	−0.56	0.0606
First dom on other	−3.773	0.0415	−3.081	0.0729
Each add. dom on other	−1.267	0.0148	−3.205	0.0667
First gen on other	−1.097	0.0146	−0.914	0.086
Each add. other on other	−0.558	0.0395	−0.434	0.0541
First gen on gen	−3.964	0.0359	−1.474	0.0881
Each add. gen on gen	−1.087	0.0883	−0.399	0.068
First dom on gen	−2.822	0.0625	−0.731	0.0771
Each add dom on gen	−1.081	0.0314	−0.524	0.0427
First other on gen	−2.792	0.0627	−0.078	0.0565
Each add other on gen	−1.305	0.0295	−0.861	0.0728
Explanatory variables	Included		Included	

The table presents the estimates from our structural model for subsamples of markets with above- and below-mean network density for markets with at least one potential tie. Variables are as defined in Table III. We define a market as a Metropolitan Statistical Area (MSA). Industry sectors are defined by the six Venture Economics industry categories. We define generalist and specialist VCs as in Table III. We restrict our analysis to VCs that operate in oligopoly markets where there are five or fewer operating dominant sector specialists, five or fewer non-dominant sector specialists, and three or fewer generalists

results also reflect a preeminent role for generalists among the various sector specialization types. One reason is mechanical—since generalists are investing in multiple sectors, they are almost certainly investing in the same sectors that the specialists are. Furthermore, generalist funds may be larger and more experienced than are specialist funds (Hochberg et al. (2010)), and thus may provide an attractive alternative funding source for startup companies even if their human capital is composed of generalist individual partners who lack specific-industry expertise (Gompers et al. (2009)).

5 Conclusion

Entrepreneurs typically view VCs as offering differentiated value-added services in addition to their otherwise functionally-equivalent capital (Hsu (2004)). Using methods that have been adapted from the empirical industrial organization literature, we examine market structure and competition in the VC industry and account for a particular type of product differentiation: the choice to be a specialist or generalist investor.

We employ a model of endogenous market structure and a dataset of smaller oligopolistic local VC markets to quantify the effects of three types of VCs—specialists in the local market's dominant industry sector, specialists in other sectors, and generalists—have on competition in VC markets. Observed type configurations of operating VCs and a game-theoretic specification of decisions regarding market presence and specialization identify parameters that represent the competitive impact of other market participants. While our approach limits our flexibility in incorporating other dimensions of VC heterogeneity and does not permit us to include the largest VC markets in our dataset, its advantage is that it allows us to conduct an analysis of competition even without detailed data on valuations, investment terms, and startup company characteristics.

Consistent with the presence of strong cooperative ties between VCs that dampen competition, we find that competitive patterns in the VC industry are markedly different from those that have been estimated for differentiated competitors in other (non-networked) industries. In other studied industries, the first competitor of each type has a greater effect than additional same-type competitors, and the effect of same-type competition is more intense than competition of any other type, such that differentiation softens competition. In contrast, in the VC industry, the incremental effect of additional same-type competitors increases as the number of same-type competitors increases. Furthermore, we find that the effects of generalist investors on specialists are substantial, and more so than the effect of same-type competitors.

These differences are concentrated in markets that exhibit relatively higher incidence of cooperative ties among operating VCs, which suggests that the presence of strong relationships amongst otherwise ostensible competitors softens competition among VCs. Overall, however, the VC market does appear to be competitive, in the sense that additional competitors of any type make markets less attractive for both same- and different-type competitors. Even if they do soften competition somewhat, networks among VC market participants likely provide offsetting benefits for entrepreneurs.

Due to the compensation structure that is prevalent in the VC industry, VC profits derive primarily from portfolio company success: directly (through carried interest) or indirectly (through fees raised from future fundraising, which in turn is dependent on past portfolio company successes). A well-networked VC market may allow for greater value-added activity on the part of the VC, and the startup companies funded by well-networked VCs have higher probabilities of both interim survival and eventual successful exit that do not derive solely from network enhancement of the ability to select investments (Hochberg, Ljungqvist, and Lu (2007)).

Acknowledgment Thanks for helpful comments and suggestions go to the editor and referees, along with Snehal Banerjee, Brett Green, Thomas Hellmann, Jiro Kondo, Brian Melzer, Josh Rauh, Paola Sapienza, Scott Stern and seminar participants at the Western Finance Association Annual Meetings, Northwestern University, the University of British Columbia, Temple University, the International Industrial Organization Conference, City University of Hong Kong, the Technion-Israel Institute of Technology and the Federal Reserve Bank of Chicago. Hochberg gratefully acknowledges funding from the Zell Center for Risk Research, the Heizer Center for Private Equity and Venture Capital and the Center for Research in Technology and Innovation at the Kellogg School of Management.

References

Bresnahan, T., & Reiss, P. (1991). Entry in concentrated markets. *Journal of Political Economy, 95*(5), 977–1009.

Bygrave, W. D. (1988). The structure of the investment networks of venture capital firms. *Journal of Business Venturing, 3*(2), 137–157.

Chen, H., Gompers, P., Kovner, A., & Lerner, J. (2010). “Buy local? The geography of venture capital. *Journal of Urban Economics, 67*(1), 90–102.

Ciliberto, F., & Tamer, E. (2009). Market structure and multiple equilibria in the airline industry. *Econometrica, 77*(6), 1791–1828.

Cohen, A. M., & Mazzeo, M. J. (2007). Market structure and competition among retail depository institutions. *Review of Economics and Statistics, 89*(1), 60–74.

Dranove, D., Gron, A., & Mazzeo, M. J. (2003). Differentiation and competition in HMO markets. *Journal of Industrial Economics, 51*(4), 433–454.

Florida, R., & Kenney, M. (1988). Venture capital, high technology and regional development. *Regional Studies, 22*(1), 33–48.

Gompers, P., Kovner, A., & Lerner, J. (2009). Specialization and success: Evidence from venture capital. *Journal of Economics and Management Strategy, 18*(3), 817–844.

Gompers, P., & Lerner, J. (1999). *The venture capital cycle*. Cambridge, MA: MIT Press.

Greenstein, S., & Mazzeo, M. J. (2006). The role of differentiation strategy in local telecommunication entry and market evolution: 1999–2002. *Journal of Industrial Economics, 54*(3), 323–350.

Hochberg, Y. V., Lindsey, L. A. & Westerfield, M. M. (2015). Resource accumulation through economic ties: Evidence from venture capital. *Journal of* Finance, forthcoming..

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *Journal of Finance, 62*(1), 251–301.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2010). Networks as a barrier to entry and the competitive supply of venture capital. *Journal of Finance, 65*(3), 829–859.

Hochberg, Y. V. & Westerfield, M. M. (2012).The size and specialization of direct investment portfolios. Working paper, Northwestern University.

Hsu, D. (2004). What do entrepreneurs pay for venture capital affiliation? *Journal of Finance., 59*(4), 1805–1844.

Kaplan, S. N., & Schoar, A. (2005). Private equity returns: Persistence and capital flows. *Journal of Finance, 60*(4), 1791–1823.

Lerner, J. (1994). The syndication of venture capital investments. *Financial Management, 23*(1), 16–27.

Mazzeo, M. J. (2002). Product choice and oligopoly market structure. *RAND Journal of Economics, 33*(2), 221–242.

Reiss, P. (1996). Empirical models of discrete strategic choices. *American Economic Review, 86*(2), 421–426.

Saxenian, A. (1994). *Regional advantage: Culture and competition in silicon valley and route 128*. Cambridge, MA: Harvard University Press.

Seim, K. (2006). An empirical model of entry with endogenous product-type choices. *RAND Journal of Economics, 37*(3), 619–640.

Sorensen, M. (2008). Learning by investing: Evidence from venture capital. Working Paper, Columbia University.

Sorenson, O., & Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology, 106*(6), 1546–1588.

Tamer, E. (2003). Incomplete simultaneous discrete response model with multiple equilibria. *Review of Economic Studies, 70*(1), 147–167.

Toivanen, O., & Waterson, M. (2005). Market structure and entry: Where's the beef? *The Rand Journal of Economics, 36*(3), 680–699.