# Specialization and Competition in the Venture Capital Industry [*] [†]

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## Abstract

An important an important type of product differentiation in the VC market is industry specialization. We estimate a market structure model to assess competition among differentiated participants in the venture capital (VC) industry. The impacts of competitor presence on profits appear markedly different than in other industries with differentiated competitors. Consistent with the presence of network effects that soften competition, these patterns are concentrated in markets that exhibit dense organizational networks among incumbent VC firms. Markets with sparser incumbent firm networks, by contrast, exhibit competitive patterns that resemble those of other, non-networked industries.



*Key words:* Venture Capital, Specialization, Product Differentiation, Competition, Networks.

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 in both among practitioners and in the academic literature. In this paper, we explore how differentiation among venture capitalists affects the profits they earn and the extent to which differentiation and competition interact to affect such profits. Employing tools from the industrial organization literature to examine market structure and outcomes in local VC markets, we find that the impact of competitor presence on profits appear markedly different than in other industries with differentiated competitors. These patterns, however, are consistent with the presence of strong VC networks that may soften competition.

Entrepreneurs typically view VCs as offering differentiated value-added services in addition to their otherwise functionally-equivalent capital (Hsu (2004)). Here, the specific VC product differentiation dimension we explore is industry specialization, which often brings deeper, specialized knowledge, resources, and relationships. A VC firm faces an interesting tradeoff when deciding whether to specialize in a particular sector or to remain a generalist (making an investment across several sectors). A firm might specialize, for example, because its principals hold sector-specific expertise that affords them advantages when selecting or managing ventures or in convincing startups to accept funding from them, rather than from a competitor. To the extent that this is true, the specialized VC may be more profitable than its local competitors who are generalists.

On the other hand, specialization may instead result because a particular sector happens to have many promising ventures in a given geographic market. In this case, the abundance of investment opportunities in that sector will likely attract several competing venture funds, resulting in higher bids or valuations for ventures. This will necessarily reduce each fund's ability

to earn high returns on investments in that sector. In such a circumstance, a VC firm might find investing (and indeed, perhaps, specializing) in less-crowded sectors preferable, to the extent that less competition makes investing in ventures more profitable, all else equal. 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. As the number of competing VCs and available investments increases, the terms of this tradeoff may intensify.

Assessing competition in the VC industry, where data on valuations, investment terms and startup company characteristics are largely unobserved, and where price and deal terms are highly customizable and arrived at through individual negotiations, is far from straightforward. Recent research in the empirical industrial organization literature, however, offers structural econometric methods for evaluating the competitiveness of markets based on easily available data such as the number of operating firms in a market. This method utilizes a discrete choice estimation model that is derived by combining a firm-level reduced-form profit function with a game-theoretic model of entry and market competition. Based on this relatively simple structure, researchers can make inferences about margins and rivalry from information about market characteristics and the number of competitors. This is a particularly attractive approach in an industry such as VC where the data that is required to perform a detailed demand and supply analysis is not available.

In addition, this approach is well-suited for assessing the effects of competition in heterogeneous product markets. If there are particular entrepreneurs who are an especially good match for a specific type of investor based on their characteristics or expertise, high returns can be maintained even in a market with many operating VCs, as only a subset may be relevant competitors.

To assess market competitiveness in the presence of the tradeoff between the potential

returns to specialization and the appeal of thick market sectors versus the benefits of reduced competition, we follow the approach of Mazzeo (2002), which extends methodology originated by Bresnahan and Reiss (1991) to the case of firms offering discrete heterogeneous product types. The data analyzed under in this approach represents the outcomes of firm decisions regarding (a) whether to enter the market and (b) which "product type" to provide given the choices of competitors. In our setting, the analogy is straightforward: VC firms decide whether or not to offer financing to startups within a particular local market and whether or not to specialize in investing in a particular industry segment. Estimates from a Mazzeo-style model measure the incremental effect of additional competitors on profits, explicitly distinguishing between the effects of firms with similar and different discrete types. In our setting, this amounts to measuring the impact of additional players on VC competition, explicitly comparing the effects that specialist and generalist investors may have within and across their groups.

We use data from a comprehensive dataset of U.S. VC funds and investments, focusing on oligopoly markets, where coordination costs are lower and concerns about competition are likely more pronounced (Hochberg, Ljungqvist and Lu (2010)). In other industries studied using this methodology, measured competitive effects exhibit certain common patterns. Additional competitors present in the market reduce the profitability of competing firms; typically, the first competitor of each type affects profitability more than additional same-type competitors. In addition, differentiation tends to soften competition, insofar as the effect of same-type competition is more intense than competition of any other type. The estimates from our structural model of the VC industry provide a striking contrast. The results do suggest that VC markets are competitive, in the sense that the presence of additional firms reduces profits. The detailed patterns of competition, however, differ starkly from those observed in other industries with differentiated

competitors. In particular, the estimates from our model suggest that the incremental effect of additional same-type competitors *increases* as the number of same-type competitors increases. Furthermore, we find that effects of generalist investors on specialists are substantial, and larger than the effect of same-type competitors.

These unique findings are nonetheless consistent with the presence of strong inter-firm co-investment networks in the VC industry, as these networks suggest the presence of cooperative relationships among VCs that may initially soften the effects of having competitors present in the market. The VC industry is characterized by strong inter-firm co-investment networks, which on the one hand appear to enhance the performance and survival of VC portfolio companies (Hochberg, Ljungqvist and Lu (2007)), but on the other hand may also act as a barrier to entry by new competitors and reduce the valuations paid to entrepreneurs (Hochberg, Ljungqvist and Lu (2010)). A local market with a single operating VC firm may find that entry of an additional VC firm has positive cooperative effects that partly offset the effect of having a competitor present in the market. Once a sufficient number of competitors enter the market, however, the positive benefit of additional potential network partners may grow smaller relative to the negative effect of additional competition for deals.

To investigate this hypothesis, we split our data into subsamples of more- and less-densely networked markets. If the relationships and cooperation among networked VC firms in a market soften competitive effects and lead to the different competitive patterns we observe in the VC market, the effect of these ties should be stronger in markets where VC firms are more densely networked. In contrast, in markets where VC firms rarely form links, and networks are sparse, we should observe competitive patterns that are more similar to those observed in other industries that lack the network activity of the VC industry. When we estimate our model separately for the

subsamples of local markets with higher and lower VC network density, we obtain results consistent with this notion: markets in which VC network density is higher exhibit the patterns described above for the full sample, while markets in which VC network density is lower exhibit competitive patterns typical of other markets that lack cooperative relationships between competitors. Our findings thus suggest the presence of positive agglomeration effects that dampen the competitive pressures of additional market entry for VCs.

Our contribution to the literature is four-fold. First, our paper contributes to the literature exploring the nature of competition in the VC market. Empirical evidence regarding competition in the VC market to date is limited. Hochberg, Ljungqvist and Lu (2010) show that in local markets, dense networks of VC co-investment activity may act as barrier to entry by new capital providers, and lead to lower valuations paid to entrepreneurs. Hsu (2004) is among the first to note that entrepreneurs view venture capitalists as offering differentiated services, and explores whether and what entrepreneurs are willing to pay to gain funding from more reputable financiers. To the best of our knowledge, our work is the first to explore the endogenous structure of VC markets and the competitive patterns in these markets, emphasizing in particular the role of heterogeneous competitors.

Second, our work contributes to an emerging literature on specialization in the VC industry. Sorensen (2008) explores the tradeoff between specialization as an exploitation strategy and exploration outside a firm's area of expertise. Gompers, Kovner and Lerner (2009) examine the relationship between specialization of individual human capital and VC firm success, taking the specialization of the VC firm as exogenous. Hochberg and Westerfield (2010) explore the tradeoff between VC fund specialization and portfolio size. In contrast, we focus here on the effects of specialization on competition in local markets.

Third, our work is related to the literature on the effects of network ties among VCs. Sorenson and Stuart (2001) explore how inter-firm ties in the VC industry affect geographic patterns of exchange. Hochberg, Ljungqvist and Lu (2007) examine the relationship between a VC firm's network position and the performance of its funds and portfolio companies, while Hochberg, Ljungqvist and Lu (2010) explore the effect of market-level VC networks on market entry and the valuations paid to entrepreneurs. Hochberg, Lindsey and Westerfield (2011) explore theories of inter-firm network tie formation in VC, including the sharing of resources across firms. Our findings provide additional insight into potential effects of this prominent feature of the industrial organization of the VC market. To the best of our knowledge, this is the first study to examine endogenous structure of markets in a networked industry and the competitive patterns in these markets, in particular in the face of differentiated competitors.

Finally, our study contributes to a large literature on market structure, product differentiation and entry in the industrial organization literature such as Seim (2006), Greenstein and Mazzeo (2006) and Cohen and Mazzeo (2007). In contrast to similar studies conducted on other industries, the VC market exhibits markedly different competitive patterns, both within- and across VC firm types.

The remainder of the paper is organized as follows. Section I describes the structural model of market structure employed in our analysis. Section II describes the sample and data, and presents descriptive statistics on the structure of local VC markets. Section III presents and discusses the estimates from our structural model. Section IV concludes.

## I. A MODEL OF ENDOGENOUS MARKET STRUCTURE IN VENTURE CAPITAL

To examine the competitive consequences of sector specialization and competition in VC markets,

we make use of the so-called "multiple-agent qualitative-response" models employed in the industrial organization literature to evaluate entry strategies and market competition (see Reiss (1996) for an overview of the empirical framework).[1] These models utilize observed data on firm decisions in a series of markets and make inferences about the profitability of firms' strategies based on the assumption that the decisions are made optimally, given competition and market conditions. In particular, these strategies are represented by discrete decisions – in our context the key decisions will reflect entry into a market (or not) and which among a small set of sector specialization strategies (specialize in the market's "dominant" sector, specialize in a secondary sector, or do not specialize) – that each VC in the market has chosen. The decisions of each individual VC are aggregated to the market level to generate an observation, which is a vector representing the discrete decisions of all the VCs in the market.

The basic intuition of the empirical approach is to estimate parameters of the profit functions underlying the firms' observed decision using inequalities implied by profit maximization. For example, we infer that a firm is profitable based on its presence in the market and that an additional market participant (i.e., one more than is observed) would not be profitable. In a competitive market, this approach is complicated by the fact that the decisions of other firms affect the profitability of the potential alternatives — for example, operating may be less profitable as the number of competitors present in the market increases. A game theoretic model is therefore used to infer individual firm profitability from an observed market structure outcome, determined

[1] 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. The theoretical basis for the use of the Herfindahl is a Cournot equilibrium with homogeneous firms, and thus is not 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.

by the choices made by interacting agents. Because our goal is to assess the competitiveness of the various sector specialization strategies for VCs, we analyze a model where each distinct specialization type has a separate function that underlies its decision making.[2]

To accommodate differentiation among competitors, we follow Mazzeo (2002) and employ a model that endogenizes product type choice as well as entry. We identify competitors as being one of three types of VCs depending on their specialization strategy (either "generalist," "dominant sector specialist" or "other sector specialist") and posit a separate profit function for VC firms of each type. This allows us to determine whether same-type competitors affect profits more than different-type competitors. We include both the number and product types of competitors as arguments in the reduced-form profit function. We treat all VCs within a given type as symmetric.[3]

More generally, we can specify the profits of a firm of type $\tau$ 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:[4]

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

The first term represents market demand characteristics that affect firm profits (note that

[2] 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).

[3] 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 the discussion of this in the results section below).

[4] This specification of the profit 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 in the profit function. 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 firm of the same type in a given market.

the effect of $X_m$ is allowed to vary by type). The $g(\theta_\tau; N_1, N_2, N_3)$ portion of the profit function 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 on profits of same-type firms and the competitive effects of firms of each of the different-types. The set of $\theta$ parameters can also be specified to capture the incremental effects of additional firms of each type. Note that the parameter vector $\theta$ varies across types; this allows the competitive effects to potentially differ by type. The estimates reported in section III reflect the following specification of the competitive-effect dummy variables:[5]

$$\begin{aligned} g_G = {} & \theta_{GG1} * \text{ presence of first generalist competitor} \\ & + \theta_{GG2} * \text{ number of additional generalist competitors} \\ & + \theta_{GD1} * \text{ presence of first dominant sector specialist competitor} \\ & + \theta_{GD2} * \text{ number of additional dominant sector specialist competitors} \\ & + \theta_{GO1} * \text{ presence of first other sector specialist competitor} \\ & + \theta_{GO2} * \text{ number of other sector specialist competitors} \end{aligned} \tag{2}$$

$$\begin{aligned} g_D = {} & \theta_{DD1} * \text{ presence of first dominant sector specialist competitor} \\ & + \theta_{DD2} * \text{ number of additional dominant sector specialist competitors} \\ & + \theta_{DG1} * \text{ presence of first generalist competitor} \\ & + \theta_{DG2} * \text{ number of additional generalist competitors} \\ & + \theta_{DO1} * \text{ presence of first other sector specialist competitor} \\ & + \theta_{DO2} * \text{ number of other sector specialist competitors} \end{aligned} \tag{3}$$

[5] 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.

$$
\begin{aligned}
g_O = \theta_{OO1} * & \text{ presence of first other sector specialist competitor} \\
+ \theta_{OO2} * & \text{ number of additional other sector specialist competitors} \\
+ \theta_{OG1} * & \text{ presence of first generalist competitor} \\
+ \theta_{OG2} * & \text{ number of additional generalist competitors} \\
+ \theta_{OD1} * & \text{ presence of first dominant sector specialist competitor} \\
+ \theta_{OD2} * & \text{ number of dominant sector specialist competitors}
\end{aligned} \tag{4}
$$

We specify the unobserved part of profits, $\varepsilon_{GDO}$, to follow an independent standard trivariate normal distribution. As such, there is no implied correlation of among the individual elements of ($\varepsilon_G$, $\varepsilon_D$, $\varepsilon_O$) within a given market, and the variance of the unobservables is the same for all types.

To proceed, we need to make an assumption about the nature of the process that generates the observed market configuration on VCs. As noted, we start by assuming that there are three possible types of VCs that could operate in a given market — generalists (G), dominant-sector specialist (D), or other-sector specialist (O).[6] Abstracting from differences among firms of the same type, firms that do enter market *m* earn $\pi_{\tau m}(N_1, N_2, N_3)$, where $\tau$ 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 the competitors that also operate in market *m*.[7] Firms that do not enter earn zero.

We estimate the model assuming that the observed market outcome is arrived at as if potential entrants of each type were playing a Stackelberg game. In such a specification, players of the various types sequentially make irrevocable decisions about entry before the next firm plays. As they make these decisions, firms anticipate that potential competitors of all types will

[6] In effect, we are assuming that the VCs have inherent types which define their subsequent choices regarding the sectors of the companies that they make investments in. To a substantial degree, the specialization choice would be made upfront when the VCs initially raise the fund. With this framing, the problem can be studied as an entry problem, and we can make the inferences as described below. Empirically, we are examining the realization of this choice each period.

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

subsequently make entry decisions once the earlier movers have committed to their choice.[8] The Stackelberg game has the attractive feature that the highest profit types will have the largest presence in the resulting market configuration. In other words, the game's outcome is observationally equivalent to what would obtain if the later entry of a higher profit type would precipitate the subsequent exit of a competitor that is not as profitable as a result of the entry. Conceptualizing competition using this game structure allows us to make inferences about the profitability of alternative market configurations based on the observed set of VCs operating in the market.

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

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

and

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

The inequalities in equation (5) formalize the assumption that firms that are operating in the market do so because they are profitable; any additional firms that might enter the market (as

[8] 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 that generate unique equilibria.

any of the three types) would not be profitable. The inequalities in (6) represent the assumption that no firm that is currently operating in the market could be profitably replaced with a firm of a different type. In other words, all the operating firms have made the appropriate entry decisions, given the specialization of their competitors.

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

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

where $(G,D,O)_m^A$ 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 $(G,D,O)^A = (1,1,1)$ for market *m*, the contribution to the likelihood function for market *m* is $\text{Prob}\left[(1,1,1)\right]$.[9]

Before leaving our presentation of the econometric model, it is worth noting the structural assumptions underlying our interpretation of the estimated θ parameters as representing the incremental effects of various competitors on profits. In particular, without data on costs, we must

[9] 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 profit function 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.

assume that VCs share a common minimum efficient scale – otherwise, we would observe ever larger VCs dominate markets rather than a positive correlation between a market's entrepreneurial activity and the number of VCs present. Data requirements and estimation tractability necessitate an assumption of abstracting away from differences among VCs other than their specialization decisions. Though each VC clearly 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 enter.[10] 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 structure outcomes. The importance of other types of differentiation will help in the interpretation of the competition parameters that we do estimate.

## II. 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 percent of all venture

[10] Some progress has been made, see Ciliberto and Tamer (2010) in more straightforward industries like airlines, where the total number of firms able to enter a market is quite small.

investments.[11] Our sample, which is also employed in Hochberg, Ljungqvist and Lu (2007), covers investments made over the period 1975 to 2003.

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 ten-year) life, the VC management 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)), resulting in a sequence of funds raised a few years apart. Startup companies seeking capital generally seek this capital from a VC firm, rather than a specific fund within that firm, and the experience, contacts and human capital acquired while running one fund typically carries over to the next fund. As entry and 'type' decisions are related to demand for capital and services from entrepreneurs, we focus here on specialization at the firm level.

When analyzing any aspect of competition among VCs, it is critical to note the role of geography in determining the match between venture capitalists and startup firms seeking capital. The nature of these relationships -- including research, due diligence, establishing personal contacts, and monitoring of portfolio companies -- makes venture capital a decidedly local industry. Furthermore, Sorenson and Stuart (2001) show that VCs tend to invest locally, lending additional support in favor of segmenting markets geographically. As a result, we explore competition at the local geographic market level, which we define as the Metropolitan Statistical Area (MSA) or Consolidated Metropolitan Statistical Area (CMSA) in which the VC firm operates. VCs operating in a particular MSA are assumed to be competitors and we proxy for the

[11] 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 distributed to investors.

industry sector specialization of VC firms based on their portfolio of startups in that MSA.[12] The relevant units of observation are the MSA-year (for markets) and the VC-market-year (for individual investing firms).

Table I summarizes our data regarding market participation at the MSA-year level. The table represents a histogram, with the frequency column indicating the number of market-year observations that contain the corresponding number of operating VC firms. 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. Indeed, about half of the market-year observations have six or fewer operating VCs. Concerns about competition in markets with smaller numbers of VC providers are likely to be larger, as smaller VC markets appear to allow for a higher likelihood of strategic coordination amongst participants (Hochberg, Ljungqvist and Lu (2010)).

In our analysis, we focus on a particularly important dimension of differentiation among VC firms – industry sector specialization. Some VC firms choose to specialize in a particular industry, while others act as generalists, investing across industries. For example, Sequoia Capital XI, a large VC fund raised in 2003, successfully invested in both shoe stores and network security firms (Zappos.com, sold to Amazon in 2009 for about $800 million, and Sourcefire, IPOed in 2007 with a market value of about $350 million). The same fund also invested in fabless semi-conductors (Xceive), network control technology (ConSentry), airline IT and services (ITA) and social networking websites (LinkedIn). In contrast, Longitude Venture Partners, a smaller VC fund raised in 2008, focuses on biotechnology investments, and its portfolio consists primarily of

[12] While entrepreneurs may consider the portfolio of past startup investments a VC firm has made in other market 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.

drug development companies.[13]

We define a VC firm as 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 five year period and has made more than one investment during that time period. Any firm making fewer than 90% of its investments in one particular sector in the market over the preceding five year period is considered a generalist. In what follows, all of our analyses are robust to changes in this threshold from 90% to 60%.

The industry sectors we consider in our analysis are the six broad industry sectors defined by Venture Economics: biotechnology, communications and media, computer-related, medical, non-high technology, and semiconductors. We provide a frequency table for the sectors of firm-level specialization in Table II. Each of the six industry categories have some VCs that specialize only in that sector, from a low of five percent in biotechnology. Just over 14 percent 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 the competitive effects of generalists, specialists in the dominant industry sector for the market, and the pool of specialists in non-dominant industry sector for the market. 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 VE) that has the greatest number of specialists in that geographic market. For example, if three VC firms in a market specialize in biotechnology and two specialize in semiconductors, we will define

[13] VC firms also differ by geographic focus, with some firms investing nationally and others focusing 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 seeking 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.

biotechnology as that market's dominant sector. VC firms in that market that specialize in a sector other than the dominant sector are then categorized as non-dominant sector specialists. We define VC firms that have made only one investment over the previous five years – and are thus vacuously specialized -- as fringe VC firms.

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 misestimate the competitive effects of the generalist investor, who 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 precisely examine their within-type competitive effects. We thus identify within-type competitive effects of specialist investors off of 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 firms we identify are most likely to be oligopolistic competitors (i.e., the set of firms possibly going after the same deals). As a consequence, we do not consider the very largest VC markets – these geographic areas typically contain many distinct submarkets that we could not identify separately

from our aggregated data. 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 market definition, 277 of the 288 MSA/CMSAs are included in the analysis. So as to avoid over-lapping time periods of competitive interactions, we restrict our data to the years 1982, 1985, 1988, 1991, 1994, 1997, 2000, and 2003. These geographic and timing restrictions allow us to better match 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.

In addition to the number and type of competitors in the market, our model includes market-level profit-shifter variables, which capture the effects of market-level characteristics on the profits of each type of firm. As a measure of market size, we use the natural logarithm of the number of VC investments in the market over the preceding five year period. To capture economic activity, we use the natural logarithm of the Gross State Product (GSP) and the natural logarithm of gross state research and development expenditures, both obtained from the Bureau of Economic Analysis. As a further control, we include the number of fringe firms operating in the market.

To allow us to distinguish between markets where cooperative ties between competitors are strong versus weak, we further compute the network density for the market, measured as the proportion of all logically possible ties among operating VC firms that are present in the undirected network resulting from VC firm co-investment in startup companies over the preceding five year period.[14] When estimating models for the full sample, we include the network density measure as a profit-shifter variable, to capture the fact that valuations appear to be lower in markets where VCs are more closely tied to each other through co-investment activity (Hochberg,

[14] Following Hochberg, Ljungqvist and Lu (2007, 2010), we construct the undirected co-investment network for year $t$ as the matrix of ties between VCs, where the cell $(i, j)$ of the matrix takes the value of one if VCs $i$ and $j$ were coinvestors in a portfolio company over the preceding five year period, and zero otherwise.

Ljungqvist and Lu (2010)).

Summary statistics for our data appear in Table III. The number of dominant sector specialist VC firms ranges from zero to five, with a mean of 0.886 per market-year in our sample, with a similar number of VC firms specializing in other, non-dominant sectors in each market-year. There approximately 3.6 fringe firms operating on average in each market year. The average market has a density of network ties among VCs of 0.27, with network density varying from zero to 1.

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. Given its composition, it makes most sense to choose the "non-high-technology" sector to be this omitted category. Based on these definitions, Table IV presents a summary of the observed market configurations in our sample. The most common configuration of the market has zero generalists, zero dominant sector specialists, and zero other sector specialists—i.e., only fringe firms.[15] The second most common configuration of the market has zero generalists, zero dominant specialists, and one non-high-technology specialized VC (defined as a non-dominant specialist, as described above). The third most common configuration has one dominant market specialist and zero competitors of either other type. The configuration with the maximum allowable number of each of the three types, (5,5,3), makes up 0.4% of our sample. Recall that this market-level ordered triple will be the dependent variable of our econometric model; the resulting estimated parameters will define the profitability of each VC type, given the specification described above.

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

## III. EMPIRICAL RESULTS

Table V presents the maximum likelihood estimates from our three-type endogenous market structure model for venture capitalist specialization. The estimated parameters allow us to compute the relative profits for each specialization strategy based on particular market conditions and in different competitive situations. To start, the estimated constants reflect the baseline attractiveness of each specialization strategy absent competition (all $\theta$ parameters multiplied by zero) and disregarding the values for all of the X-variables (all $\beta$ parameters also multiplied by zero). In this scenario, operating as a dominant sector specialist (1.283) would be relatively more attractive than operating as an other-sector specialist (0.476) or as a generalist (0.394). These figures represent predicted profits, and are normalized based on the standard normal assumption of the market-specific unobservables. We can use the estimates, therefore, to compare the relative profitability of the various types and to check whether the operating threshold is met — that is, if predicted payoffs are positive.

The estimated coefficients on the *X*-variables are broadly positive, reflecting that more firms of each type are likely to operate when these market size proxies are positive. Differences in the estimated $\beta$ parameters across types reflect how these various measures might stimulate one type of firm more than another. Dominant sector specialists, for example, do relatively better than generalists in markets with greater investment volume (market size), while investment volume hardly affects the profitability of other sector specialists at all (0.896 vs. 0.411 and 0.006, respectively). In contrast, the presence of fringe firms in the market appears to help generalists and other sector specialists, while making it less attractive to operate as a dominant sector specialist (0.389 and 0.459 vs. -0.010, respectively). Consistent with the findings in Hochberg,

Ljungqvist and Lu (2010), higher network density in the local market is associated with higher profits for all three VC types.

The left columns of Table V present the parameters ($\theta_T$) that capture the amount by which the presence of particular competitors reduces payoffs for each specialization type. For example, the estimated $\theta_{DD1}$ equals -0.502; therefore, the estimated profits of a dominant sector VC in a baseline market where the only competition is from another dominant sector VC is (1.283 – 0.502) = 0.781. Within type competition appears to be tightest for generalists ($\theta_{GG1}$ equals -0.892). The first dominant sector competitor's effect on the profits of a dominant sector specialist (-0.5017) is roughly equal to reducing the log of market size in that by 0.56, given the parameter estimate (0.8964) on the corresponding x-variable (i.e., 0.5017 = 0.56*0.8964). This reduction in market size represents 30 percent of a standard deviation of log market size (1.841), based on the markets in our sample (see Table III).

Looking 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 all three types. For example, the own-type effect of the second dominant specialist (-1.27) is greater than the first (-0.52), with the effect of each additional (-2.56) even greater. This finding contrasts with the findings in other industries (including telecommunications, lodging, banking and healthcare) in which additional competitors of the same type negatively affect profitability less 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, measuring how firms of one type affect the profits of other-type 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 $\theta$-parameters; for example, the first generalist competitor has more than three times the effect on dominant sector specialist profitability (-1.784) than the first dominant sector specialist does (-0.502) on generalist profits. 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 profits would turn *negative*: 1.283 – 1.784 = -0.501. Again, this finding is at odds with estimates of competitive effects in other types of industries in the literature, where there is a substantial product differentiation advantage reflected in the estimated parameters. For specialist VCs, avoiding competition from generalists seems to be crucially important. However, if there are already two generalists present in the market, operating as a dominant sector specialist appears to be much more attractive than operating as a third generalist (since $\theta_{GG2}$ equals -5.534).

As noted, the estimates presented in Table V suggest stark differences in the relationship between differentiation and competition in the VC industry, as compared with other industries studied using these empirical methods. In Table VI, we present estimates of a Mazzeo-style model for four industries: Motels, Telecom (CLECs), Healthcare (HMOs) and Retail Depository Institutions.[16] The motel industry estimates examine the effect of two product categories: high and low quality motels. The Telecom industry estimates examine the competitive effects of CLECs focused on the residential versus business segments. The healthcare industry estimates examine the competitive effects of HMOs with national footprints versus those with local footprints. Finally, the retail bank industry estimates examine the competitive effects of multi-market banks, single market banks, and thrifts. As shown in the table, the results of similar estimations from other industries consistently demonstrate that same-type competition is more intense than

[16] Motel industry estimates are obtained from Mazzeo (2002). Telecom industry estimates are obtained from Greenstein and Mazzeo (2006). HMO industry estimates are obtained from Dranove, Gron and Mazzeo (2003). Retail Depository Institution estimates are obtained from Cohen and Mazzeo (2007).

competition from any other type and that the first competitor of each type affects profitability more than additional same-type competitors.

One possible explanation for the differences between the competitive effects estimated for the VC industry and those estimated for other industries is unobserved within-type heterogeneity. As described in the previous section, our empirical model embodies the underlying assumption 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 commonly studied using Mazzeo-type models. Given the broad industry definitions commonly 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 possessed by VC firms.

In addition, however, these differences in competitive patterns between these industries and the VC industry are also consistent with the presence of strong inter-firm 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 both at the organizational (firm) and personal (individual partner) level. These networks serve as a conduit for both the distribution and combination of resources and information across firms (Bygrave (1988), Lerner (1994), Hochberg, Ljungqvist and Lu (2007), Hochberg, Lindsey and Westerfield (2011)).

Strong inter-VC ties offer the possibility that operating firms within a market might have symbiotic relationships that partially offset any competitive effect if, for example, stronger

network ties for a VC firm are associated with better performance and survival of portfolio companies. This interpretation could help to explain our unique result: the first VC "competitor" in a geographic market may have a positive networking impact that softens the typical competitive effect that reduces profits. Once a sufficient number of VCs enter the market, however, the positive benefit of additional potential network partners grows smaller relative to the negative effect of additional competition for deals.

VC markets vary in the extent of network ties among operating VCs, thus affording us a potential avenue to examine the hypothesis that the unique competitive patterns we estimate for the VC industry derive from the existence of some form of cooperative interaction among operating firms that offsets (to some extent) the negative effects of competition on profits. Markets in which VCs rarely form co-investment ties (low network density markets) quite likely reflect less cooperation and interaction among their participants. If cooperation and resource sharing among VCs provides a positive externality from the presence of an additional VC that dampens the competitive effects of entry, we may expect that in markets with low network density, we would observe patterns that are closer to those observed in traditional industries that lack the cooperative feature of the VC industry. Similarly, if the patterns 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 on profits. Table VII 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 described in Section 2.[17] 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. While it is still the case that the first dominant sector specialist competitor to an existing dominant sector specialist has a greater impact on profits than the second additional dominant sector specialist, each additional dominant sector specialist competitor has a much smaller effect on profits than either the first or second. In contrast, the above-mean density subsample exhibits a similar pattern to the full sample estimates, wherein the effect on profits 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, we note that the differences in competitive effects apparent 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 the sector specialization types. The results also reflect a preeminent role for generalists among the various sector specialization types. For a variety of reasons, VCs that invest in ventures across industries may be more formidable competitors. One reason, clearly, comes from the way that we have defined sector specialization – since generalists are investing in multiple sectors, they are almost certainly investing in the same sectors that the dominant sector specialists and the other sector specialists are. As a consequence, generalists and specialists are very likely competing for investment in the same startup ventures. Furthermore, generalist funds may be larger and more experienced than specialist funds

[17] As 55% of the markets in our sample have a density of zero (i.e. no network ties amongst VC firms), 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 deciding whether to form cooperative relationships with other VCs in their markets; this is a potentially important issue deserving of its own, separate, exploration.

(Hochberg and Westerfield (2010)), and thus may pose 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, Kovner and Lerner (2009)).

## IV. CONCLUSION

Entrepreneurs typically view VCs as offering differentiated value-added services in addition to their otherwise functionally-equivalent capital (Hsu (2004)). Using methods adapted from the empirical industrial organization literature, we examine market structure and competition in the VC industry, accounting 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 three types of VC firms--generalists, specialists in the local market's dominant industry sector, and specialists in other sectors—on competition in VC markets. Observed type configurations of operating VCs and a game-theoretic specification of entry behavior identify the parameters of an underlying profit function that includes the competitive impact of other market participants. While the structural nature of our approach limits our flexibility in incorporating other dimensions of VC heterogeneity, its advantage is that it allows us to conduct the analysis even without detailed data on valuations, investment terms and startup company characteristics, using counts of operating firms of the different types.

Consistent with the presence of strong cooperative ties between VC firms that dampen the competitive effects of entry, we find that competitive patterns in the VC industry are markedly different from those estimated for differentiated competitors in other (non-networked) industries.

In other studied industries, the first competitor of each type affects profitability more 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, the 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 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 VC firms.

Our findings suggest that the presence of strong relationships amongst otherwise ostensible competitors soften competition among firms. Overall, however, the VC market does appear to be competitive, in the sense that additional competitors of any type reduce profits 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 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 firm or VC market may allow for greater value-added activity on the part of the VC, and the portfolio companies funded by well-networked VC firms 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)).We leave an examination of the crucial unanswered question regarding the overall welfare effects of networking VCs to future research.

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**Table I. Number of VC Firms Operating in Local Market.**

The table presents a histogram for the number of VC firms operating in the local geographic market in a given year. Markets are defined based on Metropolitan Statistical Area (MSA) / Consolidated MSA (CMSA). We use data from every third year to avoid excessively overlapping time periods.

| Number of Firms | Freq. | Percent | Cumulative |
|---|---|---|---|
| 1 | 1,020 | 21.1 | 21.1 |
| 2 | 478 | 9.9 | 30.9 |
| 3 | 346 | 7.2 | 38.1 |
| 4 | 232 | 4.8 | 42.9 |
| 5 | 156 | 3.2 | 46.1 |
| 6 | 144 | 3.0 | 49.1 |
| 7 | 128 | 2.6 | 51.7 |
| 8 | 151 | 3.1 | 54.8 |
| 9 | 104 | 2.0 | 57.0 |
| 10 | 99 | 2.0 | 59.0 |
| 11 | 79 | 1.6 | 60.7 |
| 12 | 94 | 1.9 | 62.6 |
| 13 | 75 | 1.6 | 64.2 |
| 14 | 72 | 1.5 | 65.6 |
| 15 | 51 | 1.1 | 66.7 |
| 16 | 52 | 1.1 | 67.8 |
| 17 | 41 | 0.9 | 68.6 |
| 18 | 35 | 0.7 | 69.3 |
| 19 | 34 | 0.7 | 70.0 |
| 20 | 32 | 0.7 | 70.7 |
| 21+ | 1,419 | 29.3 | 100.0 |
| Total | 4,842 | 100.0 | 100.0 |

**Table II. VC Firm Sector Specialization.**

The table presents a histogram for the number of VC firms 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) / Consolidated MSA (CMSA). 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 firm as a specialist in a given industry sector for market *m* in year *t* if the firm has made over 90% of its investments in that sector in market *m* over the preceding five year period. We use data at three year intervals to avoid excessively overlapping time periods. We restrict our analysis to firms operating 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.

| Industry Sector | Freq. | Percent | Cumulative |
|---|---|---|---|
| Biotechnology | 111 | 5.0 | 5.0 |
| Communications and Media | 289 | 13.1 | 18.1 |
| Computer-related | 427 | 19.4 | 37.5 |
| Medical | 280 | 12.7 | 50.2 |
| Non-high Technology | 661 | 30.0 | 80.2 |
| Semiconductors | 123 | 5.6 | 85.8 |
| Generalist | 315 | 14.3 | 100 |
| Total | 2,206 | 100.0 | 100.0 |

**Table III. Summary Statistics.**

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 firm as a specialist in a given industry sector for market *m* in year *t* if the firm has made over 90% of its investments in that sector in market *m* over the preceding five year period. We define the dominant industry sector for a given market-year as the sector in which the majority of operating VC firms is specialized. A firm is defined as a generalist if it is not specialized in an industry sector. Firms 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 number of VC deals done in the market in the preceding year. State GSP and R&D 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 five year period. There are 1113 distinct market-years, involving 278 distinct MSAs. We use data at three year intervals to avoid excessively overlapping time periods. We restrict our analysis to firms operating 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.

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| # dominant sector VC firms | 0.886 | 1.349 | 0 | 5 |
| # non-dominant sector VC firms | 0.813 | 1.259 | 0 | 5 |
| # generalist VC firms | 0.283 | 0.658 | 0 | 3 |
| # fringe VC firms | 3.590 | 4.036 | 0 | 33 |
| *ln* market size | 8.401 | 1.841 | 0 | 13.113 |
| *ln* gross state product (GSP) | 11.746 | 1.063 | 8.465 | 14.179 |
| *ln* state R&D | 12.672 | 1.163 | 9.057 | 15.495 |
| network density | 0.267 | 0.378 | 0 | 1 |

**Table IV. Observed Market Configurations.**

The table presents the number (and %) of markets in the sample that have each configuration of *(# generalists, # dominant sector specialists, # non-dominant sector specialists)*. 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 firms as in Table III. There are 1113 distinct market-years, involving 278 distinct MSAs. We use data at three year intervals to avoid excessively overlapping time periods. We restrict our analysis to firms operating 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.

| # generalists | # dominant sector specialists | # non-dominant sector specialists (%) 0 | | 1 | | 2 | | 3 | | 4 | | 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 420 | *(37.7%)* | 125 | (11.2%) | 25 | *(2.2%)* | 13 | *(1.2%)* | 8 | *(0.7%)* | 4 | *(0.4%)* |
| | 1 | 90 | *(8.1%)* | 31 | (2.8%) | 9 | *(0.8%)* | 2 | *(0.2%)* | 6 | *(0.5%)* | 3 | *(0.3%)* |
| | 2 | 40 | *(3.6%)* | 21 | (1.9%) | 5 | *(0.4%)* | 7 | *(0.6%)* | 3 | *(0.3%)* | 2 | *(0.2%)* |
| | 3 | 19 | *(1.7%)* | 9 | (0.8%) | 6 | *(0.5%)* | 6 | *(0.5%)* | 2 | *(0.2%)* | 2 | *(0.2%)* |
| | 4 | 14 | *(1.3%)* | 5 | (0.4%) | 4 | *(0.4%)* | 3 | *(0.3%)* | 1 | *(0.1%)* | 0 | *(0.0%)* |
| | 5 | 8 | *(0.7%)* | 2 | (0.2%) | 4 | *(0.4%)* | 2 | *(0.2%)* | 1 | *(0.1%)* | 0 | *(0.0%)* |
| 1 | 0 | 31 | *(2.8%)* | 9 | (0.8%) | 9 | *(0.8%)* | 2 | *(0.2%)* | 0 | *(0.0%)* | 2 | *(0.2%)* |
| | 1 | 10 | *(0.9%)* | 6 | (0.5%) | 5 | *(0.4%)* | 8 | *(0.7%)* | 2 | *(0.2%)* | 1 | *(0.1%)* |
| | 2 | 6 | *(0.5%)* | 4 | (0.4%) | 4 | *(0.4%)* | 1 | *(0.1%)* | 0 | *(0.0%)* | 1 | *(0.1%)* |
| | 3 | 3 | *(0.3%)* | 4 | (0.4%) | 1 | *(0.1%)* | 3 | *(0.3%)* | 3 | *(0.3%)* | 0 | *(0.0%)* |
| | 4 | 1 | *(0.1%)* | 0 | (0.0%) | 1 | *(0.1%)* | 2 | *(0.2%)* | 2 | *(0.2%)* | 2 | *(0.2%)* |
| | 5 | 3 | *(0.3%)* | 4 | (0.4%) | 1 | *(0.1%)* | 0 | *(0.0%)* | 0 | *(0.0%)* | 0 | *(0.0%)* |
| 2 | 0 | 2 | *(0.2%)* | 1 | (0.1%) | 4 | *(0.4%)* | 0 | *(0.0%)* | 1 | *(0.1%)* | 1 | *(0.1%)* |
| | 1 | 2 | *(0.2%)* | 4 | (0.4%) | 9 | *(0.8%)* | 1 | *(0.1%)* | 1 | *(0.1%)* | 1 | *(0.1%)* |
| | 2 | 2 | *(0.2%)* | 4 | (0.4%) | 0 | *(0.0%)* | 2 | *(0.2%)* | 1 | *(0.1%)* | 0 | *(0.0%)* |
| | 3 | 0 | *(0.0%)* | 1 | (0.1%) | 3 | *(0.3%)* | 2 | *(0.2%)* | 1 | *(0.1%)* | 0 | *(0.0%)* |
| | 4 | 0 | *(0.0%)* | 1 | (0.1%) | 3 | *(0.3%)* | 0 | *(0.0%)* | 1 | *(0.1%)* | 3 | *(0.3%)* |
| | 5 | 1 | *(0.1%)* | 1 | (0.1%) | 0 | *(0.0%)* | 1 | *(0.1%)* | 1 | *(0.1%)* | 1 | *(0.1%)* |
| 3 | 0 | 1 | *(0.1%)* | 0 | (0.0%) | 0 | *(0.0%)* | 0 | *(0.0%)* | 1 | *(0.1%)* | 0 | *(0.0%)* |
| | 1 | 0 | *(0.0%)* | 2 | (0.2%) | 0 | *(0.0%)* | 0 | *(0.0%)* | 0 | *(0.0%)* | 0 | *(0.0%)* |
| | 2 | 0 | *(0.0%)* | 2 | (0.2%) | 0 | *(0.0%)* | 1 | *(0.1%)* | 1 | *(0.1%)* | 1 | *(0.1%)* |
| | 3 | 0 | *(0.0%)* | 1 | (0.1%) | 1 | *(0.1%)* | 2 | *(0.2%)* | 0 | *(0.0%)* | 1 | *(0.1%)* |
| | 4 | 0 | *(0.0%)* | 2 | (0.2%) | 1 | *(0.1%)* | 0 | *(0.0%)* | 1 | *(0.1%)* | 1 | *(0.1%)* |
| | 5 | 0 | *(0.0%)* | 0 | (0.0%) | 0 | *(0.0%)* | 0 | *(0.0%)* | 1 | *(0.1%)* | 4 | *(0.4%)* |

## Table V. Estimates of Structural Model.

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 firms as in Table III. There are 1113 distinct market-years, involving 278 distinct MSAs. We use data at three year intervals to avoid excessively overlapping time periods. We restrict our analysis to firms operating 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.

| | **θ** | **Std. Err.** | | **β** | **Std. Err.** |
|---|---|---|---|---|---|
| **Competitive Effects** | | | **Profit Shifters** | | |
| First dom on dom | -0.5017 | 0.0376 | *Dominant Specialist Sector* | | |
| Second dom on dom | -1.2713 | 0.0793 | Intercept | 1.283 | 0.3347 |
| Each add. dom on dom | -2.5685 | 0.1206 | *ln* Market Size | 0.8964 | 0.0186 |
| | | | Fringe Firms | -0.0095 | 0.0115 |
| First other on dom | -0.0161 | 0.0917 | Network Density | 0.6719 | 0.0734 |
| Each add. other on dom | -0.7089 | 0.0499 | *ln* GSP | 0.1104 | 0.0846 |
| | | | *ln* State R&D | -0.8094 | 0.0778 |
| First gen on dom | -1.7843 | 0.0988 | | | |
| Each add gen on dom | -0.8018 | 0.1036 | *Other Specialist Sectors* | | |
| | | | Intercept | 0.4763 | 0.2802 |
| First other on other | -0.7106 | 0.0439 | *ln* Market Size | 0.0059 | 0.0229 |
| Second other on other | -1.0206 | 0.0638 | Fringe Firms | 0.4285 | 0.0075 |
| Each add. other on other | -2.1321 | 0.0724 | Network Density | 0.6177 | 0.0627 |
| | | | *ln* GSP | -0.6059 | 0.0648 |
| First dom on other | 1.4589 | 0.0663 | *ln* State R&D | 0.4281 | 0.0605 |
| Each add. dom on other | -3.5859 | 0.0396 | | | |
| | | | *Generalists* | | |
| First gen on other | -4.3771 | 0.0712 | Intercept | 0.3937 | 0.1783 |
| Each add. other on other | -0.1441 | 0.094 | *ln* Market Size | 0.4111 | 0.0324 |
| | | | Fringe Firms | 0.3886 | 0.0097 |
| First gen on gen | -0.8923 | 0.0751 | Network Density | 0.3038 | 0.0954 |
| Each add. gen on gen | -5.5339 | 0.2267 | *ln* GSP | -0.1175 | 0.1053 |
| | | | *ln* State R&D | -0.3847 | 0.1025 |
| First dom on gen | -0.6551 | 0.092 | | | |
| Each add dom on gen | -0.8562 | 0.0458 | | | |
| First other on gen | -1.3078 | 0.1042 | | | |
| Each add other on gen | 0.6458 | 0.0496 | | | |

**Table VI. Model Estimates in Other Industry Settings.**

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 (CLECs), with differentiation between residential- and business-focused product types; the Healthcare industry (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. Profit shifters are included in all models but not reported for brevity.

| **Industry** | Motels | | Telecom (CLECs) | | Healthcare (HMOs) | | Retail banks | |
|---|---|---|---|---|---|---|---|---|
| **Product types** | **θ** | **Std. Err.** | **θ** | **Std. Err.** | **θ** | **Std. Err.** | **θ** | **Std. Err.** |
| **Effect on type 1 profits** | | | | | | | | |
| 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 type 2 profits** | | | | | | | | |
| 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 | - | - | -0.3696 | 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 type 3 profits** | | | | | | | | |
| 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 |
| Of 1st type 2 firm | - | - | - | - | - | - | -0.1214 | 0.1633 |
| Of additional type 2 firm | - | - | - | - | - | - | -0.0004 | 0.1031 |

## Table VII. Networked vs. Non-Networked Markets.

The table presents the estimates from our structural model for subsamples of markets with above- and below-mean network density. 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 firms as in Table III. There are 1113 distinct market-years, involving 278 distinct MSAs. We use data at three year intervals to avoid excessively overlapping time periods. We restrict our analysis to firms operating 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.

| | below-mean network density markets | | above-mean network density markets | |
|---|---|---|---|---|
| | **θ** | **Std. Err.** | **θ** | **Std. Err.** |
| **Competitive Effects** | | | | |
| First dom on dom | -0.7483 | 0.0748 | -1.3803 | 0.1923 |
| Second dom on dom | -0.7790 | 0.0944 | -2.3172 | 0.3151 |
| Each add. dom on dom | -2.1557 | 0.1561 | -0.2582 | 0.1728 |
| First other on dom | -5.2318 | 0.1026 | 0.6355 | 0.2654 |
| Each add. other on dom | -5.2868 | 0.1015 | -4.9831 | 0.1542 |
| First gen on dom | -3.1364 | 0.1797 | -4.4968 | 0.1845 |
| Each add gen on dom | -1.0358 | 0.3649 | -0.8304 | 2.2695 |
| First other on other | -0.7150 | 0.1038 | -1.6267 | 0.1590 |
| Second other on other | -1.9868 | 0.2244 | -4.8293 | 0.2374 |
| Each add. other on other | -2.2905 | 0.0752 | -0.9918 | 0.1567 |
| First dom on other | -0.5776 | 0.2233 | 0.5140 | 0.2878 |
| Each add. dom on other | -0.2506 | 0.1169 | -4.6042 | 0.1650 |
| First gen on other | 0.3924 | 0.3563 | -2.3357 | 0.2815 |
| Each add. other on other | -1.9512 | 0.3641 | -1.8195 | 3.6780 |
| First gen on gen | -3.5051 | 0.2126 | -4.9770 | 0.2849 |
| Each add. gen on gen | -2.7342 | 24.9159 | 0.5698 | 1.0129 |
| First dom on gen | 1.4050 | 0.2622 | -1.6880 | 0.3695 |
| Each add dom on gen | -2.2724 | 0.1479 | -1.2431 | 0.6639 |
| First other on gen | 0.4473 | 0.2485 | -1.5926 | 0.3644 |
| Each add other on gen | -0.7514 | 0.057 | 0.3462 | 0.2336 |
| **Profit Shifters** | Included | | Included | |