The Size and Specialization of Direct Investment Portfolios[*]

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PRELIMINARY AND INCOMPLETE

Abstract

In much of the investments literature, specialization is assumed to enhance productivity and communication, and so size and specialization are complements. In the venture capital (VC) industry, we observe the reverse: VCs with larger portfolios tend to be less specialized. We present a model of portfolio size and specialization in which specializing increases average profitability for any project undertaken, but it excludes a VC from projects outside its area of specialization. Because portfolio returns are driven by extreme right tail events, a fund must secure access to a large deal flow to support a large number of investments, and so large funds must generalize. Using a dataset of U.S. VC investments between 1980 and 2004, we provide empirical evidence that supports the predictions of the model: larger portfolios are associated with less industry and geography specialization; positive factors such as greater experience are associated with larger and more general portfolios; negative factors such as a higher ex-ante probability of startup failure are associated with smaller, more specialized portfolios. Our model and findings support the notion that funding a portfolio of projects in a setting where deal identification is critical differs substantially from funding a portfolio of projects within a firm.

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1 Introduction

There is a general presumption in economics and finance, since at least Adam Smith, that specialization enhances productivity and is thus an important driver of value. By focusing efforts on a limited range of activities, an agent's human capital grows more rapidly, and he or she can better exploit comparative advantage or economies of scale. One might expect this logic to hold for firms that fund nascent businesses: the skills involved in building up, for example, an internet business or a biotechnology business are very different, and gathering information and experience are very important. This might lead us to expect that larger and more experienced venture capital firms would choose to specialize their operations and portfolio.

As we show, however, larger and more experienced venture capital (VC) firms tend to be generalists: they invest in a wide range of industries and geographical areas. Size and scope appear to be complements across all both these dimensions of specialization. In this paper, we present and test a model of project selection that explains why size and specialization are substitutes. Any factor that increases the returns to VC activity – higher skill, a lower cost of capital, a higher success rate – must induce a VC to choose to fund more projects and thus to generalize, while any factor that decreases the returns to VC activity – such as money chasing deals or higher probability of project failure – must induce a VC to choose to fund a smaller portfolio and thus to be more specialized.

To gain intuition for the model, consider a generic example of project selection and exploitation. There are two distinct steps: one must first select the proper project to undertake and one must then exploit human and physical capital to develop the project effectively. Specialization can have two competing effects. The first is that it allows one to better exploit existing opportunities. The second is that specialization can reduce the number of projects one can undertake. If all potential projects are similar, then the value of properly exploiting a project are much higher than the value of finding the right project to undertake. However, if the reverse is true, and some projects are vastly more valuable than others, then one must be able to sift through potential projects to find the most desirable. "Fat tails" make selecting from a large set of projects the key to value.

Venture capital investments fall squarely into the "fat tails" group: Sahlman (1990) describes the returns to venture capital investments and finds that 34.5% of money invested returned at best a partial loss, while 6.8% of money invested was responsible for nearly 50% of the final VC portfolio value. Ljungqvist and Richardson (2003) document nearly three-quarters of VC portfolio companies are written off completely, suggesting that a small proportion of VC investments account for the majority of venture fund returns. Given the low unconditional success rate for the average portfolio company, a critical activity for a venture capital firm is finding the right deal, and therefore a critical asset is access to *deal flow* (Hochberg, Ljungqvist, and Lu (2007)).[1] In this type of setting, despite its ability to enhance *exploitation* of projects, specialization can be a hindrance because it prevents a VC from being able to undertake high-potential investments that fall outside the fund's area of expertise or focus. Size and specialization are substitutes because a large VC must have the deal flow to support finding enough high quality projects to fund, and so a large VC must be less specialized.

We present a parsimonious model of deal selection and improvement in which a VC firm makes two choices: the size of the firm (number of investments) and the degree of specialization. Specialization allows for two advantages. The first is that it improves the payoff to the VC of any given project if that project is eventually successful. We assume that the payoff to a successful project is the sum of the base profitability of the idea plus the value of the development and value-added support provided by the VC. Specialist firms are better able to develop projects. The second advantage to specialization is that it improves the VC's

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[1] The VC literature typically attributes two important activities to VCs: deal selection and value-added support. Sorensen (2006) shows that the ability to select projects contributes an significant portion of VC returns, on the order of 60%, with the remainder attributed to value-added activities, and Hochberg, Ljungqvist, and Lu (2007) additionally emphasizes the importance of access to deal flow for VC returns. Hellmann and Puri (2000), Hellmann and Puri (2002), Hochberg, Ljungqvist, and Lu (2007), Lindsey (2008) and Hochberg (2008) present evidence on value-added support activities by VCs.

ability to reclaim or reuse human capital from a failed project. We assume that there are certain knowledge spill-overs, even from unsuccessful projects, and a specialist VC is better able to capture these spill-overs. Project profitability is then further modified by exogenous parameters, such as the VC's skill.

The assumed disadvantage to specialization is that a specialist VC cannot evaluate and develop all possible projects. Thus, if a VC can potentially assess N projects, a specialist can only act on some fraction of those N, with the fraction declining in the degree of specialization. If a VC has chosen to raise funds for M projects, a specialist VC will be choosing the M best projects to develop from a smaller pool. This drives down, perhaps by a great deal, the underlying value of the projects the VC will undertake. When the distribution of projects is sufficiently fat-tailed, as we assume, the size of the pool is a controlling factor, overwhelming the specialist's advantage in developing a project once it is found. Thus, size and specialization are complements, and a VC that chooses to raise a large fund will also choose to generalize operations in order to gather the deal flow required to support a large fund. By similar logic, factors which increase the attractiveness of venture investment, such as skill and lower cost of capital, will induce a VC to choose to fund more projects and thus to generalize, while factors that decreases the attractiveness of VC activity, such as greater riskiness of deals, will induce a VC to choose to fund a smaller portfolio and thus to be more specialized.

We test a number of the model's main empirical predictions in a large dataset consisting of U.S. Venture capital funds raised over the period 1980 to 1999. Our empirical evidence is consistent with the predictions of the model. Size and specialization appear to be substitutes: larger VCs are less specialized, and more specialized VCs have smaller portfolio size. Factors such as experience, which can be considered a proxy either for higher skill or for lower cost of capital, decrease specialization and are associated with larger portfolio size. Factors such as "money chasing deals" or investment in earlier stage companies, which decrease the probability of portfolio company success, are associated with greater specialization and smaller portfolios.[2]

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[2] As a caveat, we note that our model and tests determine specialization based on a firm's actual investment

Our work provides an initial set of insights both into how VC portfolios are structured, and into the frictions that affect the choice of a VC to specialize along a particular dimension or not. The nature of the VC industry makes it particularly useful for studying issues of internal capital markets and firm scope or specialization. There is considerable heterogeneity in how VC firms are organized, and detailed data is available to the researcher on the composition of VC portfolios as well as the outcomes of the individual investments. VCs invest in multiple entrepreneurial companies per fund, with the knowledge that only a few of these projects will survive to successful exit. Resources and funds held in reserve are redistributed from poor opportunities to successful ones as the companies grow and uncertainty is resolved. VC portfolios also vary widely in size, with some VCs choosing to invest in many startups, and others choosing to keep their portfolios small. Furthermore, some VC firms choose to specialize in a particular industry or region while others choose to generalize across industries or invest across wider geographical boundaries.

The predictions of our model and our empirical implications and findings differ from the findings in the internal capital markets literature. This supports the notion that funding a portfolio of projects in a setting where deal identification is critical, such as venture capital, is very different from funding a portfolio of projects within a firm. For example, we find that the more experienced funds are generalists, whereas Lang and Stulz (1994) find that for diversified firms there is a conglomerate discount. Maksimovic and Phillips (2002) present theory and evidence that the conglomerate discount and conglomerate growth patterns are consistent with optimal behavior for firms when differential productivity and project development are the key variables of interest. In addition, Stein (1997) shows how specialization can enhance a firm's ability to pick winners among its existing projects, while Inderst, Mueller, and Münnich (2007) and Fulghieri and Sevilir (2008) show how specialization and/or capital rationing can enhance entrepreneurial effort. These latter papers focus on project development and ask

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activity. Unlike Gompers, Kovner, and Lerner (2009), we cannot observe the human capital structures within a generalist organization. Thus, we do not distinguish between generalist firms that are comprised of generalist individual partners, and generalist firms comprised of specialized individuals.

questions about optimal information gathering and incentives, and do not account for deal flow constraints imposed by specialization. By contrast, our model incorporates the fact that the VC industry is one in which initial project selection is critical, and as a consequence, our predictions differ significantly from those in papers that do not account for deal flow constraints.

Our work is also related to an emerging literature on VC fund and firm organization and specialization. Gompers, Kovner, and Lerner (2009) examines the relationship between specialization and success, focusing in particular on the difference between generalist firms who employ generalist individuals and generalist firms that employ specialist individuals. Hochberg, Mazzeo, and McDevitt (2009) examine the competitive structure of venture capital markets and the the effect of specialization on competition within markets. Bhagwat and Hochberg (2009) examine the matching of specialist and generalist firms to portfolio companies. Closest to our work is Fulghieri and Sevilir (2008), who consider the choice of VC size and scope when deal flow constraints are not present.

The remainder of the paper is structured as follows. Section 2 presents our model. Section 3 describes the empirical predictions generated by the model. Section 4 describes the data, and Section 5 presents our empirical analysis. Section 6 discusses and concludes.

2 The Model

In this section, we will model the project selection for a single venture capital firm or fund. The VC will choose both the size and scope of the fund's activities: how many entrepreneurial projects to finance and to what extent to specialize the fund's activities. The key intuition is that while specialization increases a firm's ability to develop a particular entrepreneurial project, specialization reduces the set of projects that a firm can undertake. Since VCs find profitable entrepreneurial projects rather than creating them, the size of the set of projects that a VC can undertake is the key to the quality of the projects the VC actually finances. As we demonstrate, this fact implies that size and scope are complements (size and specialization are substitutes), and so any variable that increases the returns to venture finance will also decrease the chosen level of specialization for a given VC.

2.1 Projects and Agents

There are two types of agents: entrepreneurs with projects that require funding and venture capitalists with financial and human capital. The pool of entrepreneurial projects is large and each one has an associated quality Δ_i drawn from the same distribution with cdf F: $\Delta_i \sim F(\Delta)$ with $F(0) = 0$.[3] We assume that no one knows a given project's type and thus initial information is symmetric. We will also assume that the Δ_i are normalized to the portion of the project's payoffs that can be claimed by the VC, as opposed to by the entrepreneur.

Before identifying any projects, a venture capitalists must raise funds and choose which human capital (project managers) to employ and develop. As is the case in reality, the timing of fund raising in our model is important: a VC must raise funds *before* it identifies projects to undertake. We assume that there is an un-modeled information asymmetry problem between VC firms and the capital markets, so that raising capital takes time. Thus, a desirable project will be found and funded by someone else before the initial VC can return with additional funds.

Thus, the VC makes two choices. First, by raising funds, a VC chooses how many projects can be funded. Since all projects are ex-ante identical, we say the VC has funds for M projects. We will assume that the cost of raising this capital is equal to $M\theta$.

Second, a VC chooses the level of specialization: $\phi \in [0, 1]$. Intuitively, a specialized VC is better able to apply human capital to prospective projects and better able to capture human capital from failed projects. However, a specialized VC cannot consider as wide a

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[3] $F(0) = 0$ implies that $\Delta_i > 0$ and so projects cannot produce negative gross cash flows to investors. The most a VC can lose is his investment.

range of possible start-ups – the investment opportunity set is smaller. The first benefit from specialization is then that a successful project pays off $\Delta_i + \phi$: specialists have higher average profitability for any given project. The second benefit is that the VC is able to recover *all* of their specific human capital (ϕ) if a project fails, whereas they can only recover a fraction $\mu < 1$ of the base value of the project.

Not all projects are successful: given funding, the probability of success is $\alpha \in (0,1]$. The base ability of a venture capitalist is ψ, and so the gross payoff to the VC given a particular value for Δ_i for successful funded project is $\psi\left(\Delta_i + \phi\right)$. If the project fails, then the VC is still able to recover $\psi\left(\mu\Delta_i + \phi\right)$ in value. Thus the, expected gross payoff to a project given Δ_i is

$$\psi\left(\left(\alpha + (1-\alpha)\mu\right)\Delta_i + \phi\right). \tag{1}$$

Next, we consider the pool of projects that a venture capitalist can potentially finance. We assume that a VC sees N different projects. However, the VC can only evaluate and undertake at most $\llcorner(1-\lambda\phi)N\lrcorner$ of these projects: the more specialized a VC is, the more projects are outside his or her capabilities. $\llcorner(1-\lambda\phi)N\lrcorner$ represents the VC's potential *deal flow*, where $\lambda < 1$ measures the cost of specialization to deal flow, and the $\llcorner$ and $\lrcorner$ notation indicates the greatest integer below $(1-\lambda\phi)N$.

Upon evaluating the $\llcorner(1-\lambda\phi)N\lrcorner$ projects, a VC will choose the M best projects to undertake. Thus, we are interested in order statistics on Δ. Denote by $\mathrm{E}\left[\Delta_{n,m}\right]$ the expected value of the mth highest value of Δ picked from a total of n i.i.d choices. Thus, the VC's expected payoff is

$$\psi\left(M\phi + (\alpha + (1-\alpha)\mu)\sum_{j=1}^{M}\mathrm{E}\left[\Delta_{\llcorner(1-\lambda\phi)N\lrcorner,j}\right]\right) - M\theta \tag{2}$$

2.2 A Functional Form

To continue, we need to make some specification of the distribution for Δ in order to find and describe the VC's optimal choices. While closed form solutions for order statistics can be extremely messy, they follow certain basic rules, which we can exploit. Thus, we will label $\sum_{j=1}^{M} \mathrm{E}\left[\Delta_{\llcorner(1-\lambda\phi)N\lrcorner,j}\right]$ by the function G and assign it three properties common to order statistics of different distributions:

Asssumption 1 (Cumulative Order Statistics) *The function $G(n,m)$ is the sum of project values when the best m projects are pulled from a group of n potential choices:*

$$G(n,m) = \sum_{j=1}^{m} \mathrm{E}\left[\Delta_{n,j}\right]. \tag{3}$$

We will assume that $G(n,m)$ is

- *increasing and concave in m: $(G(n,m) - G(n,m-1))$ positive and declining in m.*
- *increasing and concave in n: $(G(n+1,m) - G(n,m))$ positive and declining in n.*
- *super-modular in (n,m),*[4] *with*

$$\left[(G(n+1,m) - G(n+1,m-1)) - (G(n,m) - G(n,m-1))\right] > \frac{1}{(\alpha + (1-\alpha)\mu)\,\lambda(n+1)}.$$

The first two properties are basic properties that all sensible distributions (for which moments exist) will fulfill. A VC picking picking m projects from a pool of n choices will always pick the m best projects. Thus, the $m+1$th project to be added is always worse than the first

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[4] See, for example, Athey (2002). Super-modularity means that the returns to increasing n increase in m, and vice versa. For differentiable functions, super-modularity is equivalent to $\frac{\partial^2}{\partial n \partial m} G(n,m) > 0$. We require in addition that the cross effect have a lower bound of $\frac{1}{(\alpha+(1-\alpha)\mu)\lambda}$ rather than zero. As we show below, this is often equivalent to assuming that a given distribution has "fait tails".

m. Since projects will not produce a negative gross cash flow to the VC (before accounting for the cost of capital), each additional project adds to the gross payoff, but at a decreasing rate.

Similarly, we can consider adding one potential project to a pool of n projects, from which the VC will pick the best m. If this new $n+1$th project is worse than the m already selected, then the VC gains nothing. However, if this project is better, than the VC benefits from an expanded pool by substituting the worst existing project for the new one. Thus, each additional choice adds to the expected gross payoff. As the pool of potential choices becomes very large, only the very best projects are undertaken (for a fixed m), and so the probability that any new choice will be good enough becomes very small. Thus, each addition choice adds a declining marginal value.

The final property is a cross effect between n and m. It says that as the choice set (n) of the VC increases, the marginal value of each new project undertaken (m) also increases. When the total number of choices is higher, the total number of good choices is also higher, and so the value of the mth project must increase in expectation. The $\frac{1}{(\alpha+(1-\alpha)\mu)\lambda(n+1)}$ term ensures that this marginal increase stays above a minimum level. Loosely, this means that the distribution of projects has a right tail that is "fat enough".

In fact, venture capital investments do seem to fulfill the "fat tails" requirements. Sahlman (1990) describes the returns to venture capital investments from 1969 through 1985. He notes that 34.5% of money invested went to investments that were at best a partial loss and that 6.8% of money invested was responsible for nearly 50% of the final value of investments. Ljungqvist and Richardson (2003) document that nearly three-quarters of VC portfolio companies are written off completely, while only 13% or so of investments return a multiple of three or more times invested capital over the ten to twelve year life of the fund, further supporting the notion that a small proportion of VC investments account for the majority of venture fund returns. Indeed, it is commonly accepted in the VC community that fund returns are often driven by merely one or two portfolio company successes out of an entire portfolio of investments.

To illustrate possible distributions that would meet the order statistic properties described in Assumption 1, we provide three example distributions and their associated G functions:

Example 1 (The Exponential Distribution) *Assume that the* Δ_i *are distributed exponentially:* $F(\Delta) = 1 - e^{-\frac{1}{\beta}\Delta}$. *Then the Renyi representation theorem on order statistics states that* $\mathrm{E}\left[\Delta_{n,m}\right] = \beta \sum_{k=m}^{n} \frac{1}{k}$, *and so*

$$G(n,m) = \sum_{j=1}^{m} \mathrm{E}\left[\Delta_{n,j}\right] = \beta \sum_{j=1}^{m} \sum_{k=j}^{n} \frac{1}{k} \tag{4}$$

Then we have

$$\begin{aligned}
(G(n,m) - G(n,m-1)) &= \beta \sum_{k=m}^{n} \frac{1}{k} \\
(G(n+1,m) - G(n,m)) &= \beta \frac{m}{n+1} \\
\left[(G(n+1,m) - G(n+1,m-1)) - (G(n,m) - G(n,m-1))\right] &= \beta \frac{1}{n+1}
\end{aligned}$$

So, if $\beta > \frac{1}{(\alpha + (1-\alpha)\mu)\lambda}$, *then all the required conditions on* G *are met.*

Example 2 (Power Law Distribution) *Assume that the* Δ_i *are distributed according to a power law:* $F(\Delta) = 1 - x^{-\frac{1}{\beta}}$ *for* $\beta < 1$, *defined on* $\Delta \in [1, \infty)$. *Then* $\ln(\Delta)$ *has an exponential distribution with scale parameter* $\frac{1}{\beta}$. *The Renyi representation theorem on order statistics states that*

$$\mathrm{E}\left[\Delta_{n,m}\right] = \mathrm{E}\left[\exp\left(\ln\left(\Delta_{n,m}\right)\right)\right] = \mathrm{E}\left[\exp\left(\beta \sum_{k=m}^{n} \frac{x_k}{k}\right)\right] = \prod_{k=m}^{n} \mathrm{E}\left[\exp\left(\beta \frac{x_k}{k}\right)\right] = \prod_{k=m}^{n} \frac{k}{k-\beta}$$

where the x_k *are i.i.d. standard exponential variables. Then,*

$$G(n,m) = \sum_{j=1}^{m} \mathrm{E}\left[\Delta_{n,j}\right] = \sum_{j=1}^{m} \prod_{k=j}^{n} \frac{k}{k-\beta}. \tag{5}$$

Then we have

$$\begin{aligned}(G(n,m)-G(n,m-1)) &= \prod_{k=m}^{n}\frac{k}{k-\beta}\\ (G(n+1,m)-G(n,m)) &= \left(\frac{n+1}{n+1-\beta}-1\right)G(n,m)\\ \left[(G(n+1,m)-G(n+1,m-1))-(G(n,m)-G(n,m-1))\right] &= \left(\frac{n+1}{n+1-\beta}-1\right)\prod_{k=m}^{n}\frac{k}{k-\beta}\end{aligned}$$

To fulfill all the required conditions on G, we simply require that β be above some minimum value β^*.

Example 3 (The Uniform Distribution) *Assume that the Δ_i are distributed uniformly: $F(\Delta) = \frac{\Delta}{\beta}$ for $\Delta \in [0,\beta]$. Then the Renyi representation theorem on order statistics states that $\mathrm{E}\left[\Delta_{n,m}\right] = \beta\frac{n-m+1}{n+1}$, and so*

$$G(n,m) = \sum_{j=1}^{m}\mathrm{E}\left[\Delta_{n,j}\right] = \beta\left(m - \frac{m(m+1)}{2(n+1)}\right) \tag{6}$$

Then we have

$$\begin{aligned}(G(n,m)-G(n,m-1)) &= \beta\frac{n-m+1}{n+1}\\ (G(n+1,m)-G(n,m)) &= \beta\frac{m(m+1)}{2(n+1)(n+2)}\\ \left[(G(n+1,m)-G(n+1,m-1))-(G(n,m)-G(n,m-1))\right] &= \beta\frac{m}{(n+1)(n+2)}\end{aligned}$$

Then, since $m \geq 1$, if $\beta > \frac{1}{(\alpha+(1-\alpha)\mu)\lambda}(n+2)$, then all the required conditions on G are met.

In all three examples, β is a measure of the scale of the distribution. When β is larger, the distribution has its mass pushed into the tail. Thus, a large β means that the best project will likely be drawn from further out in the now larger tail.

We illustrate the G function for the power law distribution in Figure 1.

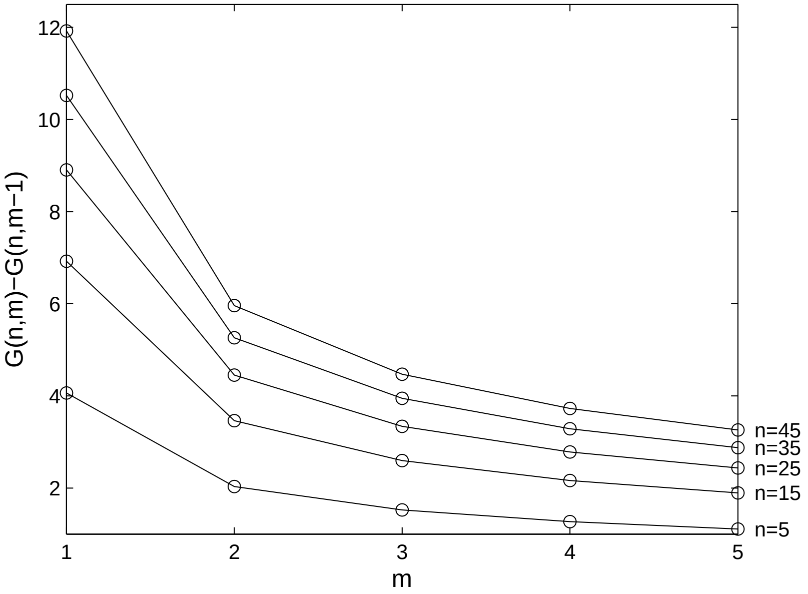

Figure 1: The marginal value to funding an additional project: $G(n, m) - G(n, m-1)$. The plot is generated using the power law distribution (5) with $\beta = 1/2$, displayed as a function of m for different values of n.

2.3 Comparative Statics

We now have an expression for the total profits of a VC firm or fund:

$$\pi(\phi, M) = \psi\left[M\phi + (\alpha + (1-\alpha)\mu)\, G\left(\llcorner(1-\lambda\phi)N\lrcorner, M\right)\right] - M\theta \tag{7}$$

To gain intuition for how the choice of specialization (ϕ) affects the VC's investment opportunities, we will treat G as if it were a continuous function, so that we can take "approximate derivatives".

$M\phi + (\alpha + (1-\alpha)\mu)\, G\left(\llcorner(1-\lambda\phi)N\lrcorner, M\right)$ represents the VC's deal flow quality – the total expected value of its M best projects, including the benefits of specialization – and is increasing and concave in the number of deals examined and the number of deals undertaken.

ϕ represents specialization, which is a choice of production (deal flow) technology. The advantage of a higher level of specialization is that the base profitability of any given project increases by an amount ϕ, and this value is recoverable even if the project does not pay off. However the disadvantage of choosing high ϕ is that the VC faces more rapidly decreasing returns to scale. The marginal value of an additional project is $\psi\left[\phi + (\alpha + (1-\alpha)\mu)\, G_M\right] - \theta$, and so the change in marginal product as ϕ increases is proportional to

$$1 - (\alpha + (1-\alpha)\mu)\, \lambda N G_{n,M} < 0.$$

This cross effect – the change in the marginal value of a new project as ϕ increases – is negative by the properties of order statistics detailed in Assumption 1. Since the marginal value of additional projects is declining in specialization (ϕ), size and specialization must be substitutes.

Any parameter that makes investments as a whole more attractive must lead VCs to invest in more projects. Following the logic of substitution, they must become generalists to gather the deal flow necessary to support a high level of activity. Thus, we expect size to increase and specialization to decrease when projects are more likely to pay off (α), when failed projects are easier to recover (μ), when VCs are more skilled (ψ), and when potential deal flow is higher (N). We expect that VCs which face a high cost of capital (θ) will choose more specialized and fewer projects. More formally:

Proposition 1 *ϕ and M are substitutes: Holding all else equal, if the VC were forced to increase ϕ or M, it would choose to reduce the other.*

In addition, we have the following comparative statics:

$$\frac{\partial}{\partial\psi}\phi^* \leq 0 \qquad \frac{\partial}{\partial\psi}M^* \geq 0 \tag{8}$$

$$\frac{\partial}{\partial\alpha}\phi^* \leq 0 \qquad \frac{\partial}{\partial\alpha}M^* \geq 0 \tag{9}$$

$$\frac{\partial}{\partial\theta}\phi^* \geq 0 \qquad \frac{\partial}{\partial\theta}M^* \leq 0 \tag{10}$$

$$\frac{\partial}{\partial\mu}\phi^* \leq 0 \qquad \frac{\partial}{\partial\mu}M^* \geq 0 \tag{11}$$

$$\frac{\partial}{\partial N}\phi^* \leq 0 \qquad \frac{\partial}{\partial N}M^* \geq 0 \tag{12}$$

Proof. Maximizing (7) is equivalent to maximizing

$$[M\phi + (\alpha + (1-\alpha)\mu)\, G\left(\llcorner(1-\lambda\phi)N\lrcorner, M\right)] - M\frac{\theta}{\psi}. \tag{13}$$

The assumptions on G imply that this is super-modular in $(M, -\phi, \psi, -\theta)$ and $(M, -\phi, \alpha, \mu, N)$. Topkis's theorem then proves the comparative statics.[5] ■

3 Predictions

To derive predictions from our model, we will look across situations and see how they induce the choice variables for specialization and portfolio size, ϕ and M, to change.

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[5] Remember that super-modularity of $f(x, y)$ in (x, y) means that the return to increasing x goes up with y. Intuitively, if the returns to x go up with y, then an optimizing agent should do more x when y is plentiful. To see this mathematically, assume f is continuous. Then super-modularity is is equivalent to stating $f_{xy}(x, y) > 0$. To see that this implies that optimal choice of x is increasing in y, we examine the first order condition on x: $f_x(x^*(y), y) = 0$. Using the implicit function theorem, $\frac{\partial}{\partial y}x^*(y) = -\frac{f_{xy}}{f_{xx}}$. Since the denominator must be negative for an optimum to exist, $f_{xy}(x, y) > 0$ implies $x^*(y)$ is increasing in y. Topkis's theorem proves this result when f is defined only on a (possibly discrete) lattice.

3.1 Across VCs

For our first three predictions, we will follow the simple logic of substitution. First, from Proposition 1 above, we have

Prediction 1 *Generalists VCs will have larger portfolios.*

Furthermore, anything that makes VC investments more attractive or profitable will induce VCs to invest in more projects. Then, the VC must be a generalist in order to have the deal flow required to find a large number of good projects. Thus, looking across skill (ψ), we have:

Prediction 2 *More skilled VCs are less specialized, with larger portfolios.*

Conversely, when all investments are constrained because a VC or the VC industry faces a high cost of capital, then the VC will choose to take on only a small number of projects and to specialize as a result. Thus, looking across cost of capital (θ), we have:

Prediction 3 *VCs with a higher cost of capital are specialists.*

Formally, the model does not distinguish between the effects of cost of capital and of skill. To see this, observe that in (13) θ and ψ appear together. Thus, we will be satisfied with empirical proxies that represent both high skill and low cost of capital.

Traditionally, the VC literature has used VC experience as a proxy for skill: in order to be able to continue participating as an investor in the industry, the VC must be able to raise sequences of overlapping funds, and the ability to raise a follow-on fund is increasing in the VCs past performance, which likely reflects (to some extent) a VC's inate skill (Hochberg, Ljungqvist, and Vissing-Jorgensen (2009). Thus, VC parent firm experience, as well as the sequence number of the fund, represent plausible proxies for VC skill – greater experience and higher fund sequence numbers suggest the VC has performed well enough consistently, over a sequence of funds, that he is likely of high(er) skill. Similarly, since experience and fund sequence number can also be taken as plausible proxies for cost of capital – there is likely to be less uncertainty about the skill level of a VC firm that has been in existence for some time and has a long track history of returns, relative to a newer VC with a shorter track history. Therefore, using experience as a proxy for skill and lower cost of capital, we can predict that:

More experienced VCs are less specialized, with large portfolios.

3.2 Across Investments

While the first set of predictions looks across VC firms, we can also look potential investments and investment conditions. Not all investments have the same characteristics: some may have higher probabilities of failure $(1-\alpha)$ than others. This makes the investment less desirable. Following the logic of substitution, fewer investments will be undertaken and the VCs that undertake earlier round investments will be specialists.[6] Looking across the probability of failure $(1-\alpha)$, we find

Prediction 4 *When the probability of failure is higher, VCs will choose to specialize more and to undertake fewer projects.*

While we cannot observe the underlying ex-ante probability of success for any individual portfolio company investment, the literature provides us with a number of possible ways to empirically examine this prediction. Portfolio companies differ in systematic ways: some may be early round, early stage investments, where uncertainty of outcome is high, while others are later-stage investments, where much of the uncertainty has been resolved. Early rounds

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[6] In the model α is not a choice variable – since α is the probability of success, all VCs would pick $\alpha = 1$. However, one could alter the model so that more speculative projects were on average more profitable (to account for risk). As long as such a modification did not end the current $(\alpha, 1-\phi, M)$ super-modularity, then α^* will be complement to M^* and a substitute for ϕ^*. Thus, even endogenously, the specialists will choose investments with a higher likelihood of failure.

are more speculative and so the probability of failure $(1 - \alpha)$ for any given attempt is higher. Thus, we predict that

Using round as a proxy for the probability of failure, VCs that invest primarily in early stage investment will be smaller and more specialized.

Additionally, Gompers and Lerner (2000) suggest that as inflows into the VC industry increase, "money chasing deals" results, whereby due to increased competition for a limited number of attractive investment opportunities leads to prices being bid up, and more marginal projects being funded, which may in turn have lower probabilities of success (α). Thus, we predict that

As inflows into the VC industry increase, VCs will choose to specialize, and will have smaller portfolios.

3.3 Across Scales

Different venture capital markets have different scales. For example, the number of potential entrepreneurs varies geographically, by industry, etc. In doing our analysis, we can look across these heterogeneous markets. Markets with less prospective deal flow (smaller N) should have smaller VC fund portfolios. This, in turn, implies that they will be specialists.

Prediction 5 *Between markets with similar observable characteristics, markets where VCs see less deal flow will have more specialists.*

In addition, the more narrow we make our sample, the more similar potential deals become. This exogenous (econometrician imposed) specialization of sample implies that human capital will be inherently more redeploy-able (higher μ) within the more limited sample. For example, let us consider specialization in geography for two samples: the US as a whole, and the US technology industry. Because human capital is inherently more re-deployable within the same industry, there are more spillovers between projects, which increases the returns to projects. This, in turn, produces generalists.[7] So, within the US technology sample, VCs will generalize across geography more than in the entire US sample.

Prediction 6 *The more the econometrician limits the sample based on observable characteristics (e.g. region, industry, etc), the more participating firms will be generalists across other dimensions within the smaller sample.*

In what follows, we focus on testing the first four predictions of the model. In future versions of the paper, we hope to test the remaining predictions directly.

4 Data

The data for our analysis come from Thomson Financial's Venture Economics database. Venture Economics began compiling data on venture capital investments in 1977, since backfilled to the early 1960s. 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 (Ljungqvist, Richardson, and Wolfenzon (2005)). In the second half of the fund's life, successful portfolio companies are exited via IPOs or sales to other companies generating 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.

We concentrate solely on investments by U.S. based VC funds, and exclude those by angels and buyout funds. We distinguish between funds and firms. While VC funds have a limited (usually ten-year) life, the VC management firms that manage the funds have no predetermined

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[7] It also means that within the sample, the VCs will be larger. However, without further information, it is not clear how to compare VC size across differently sized (and exogenously determined) subsamples.

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. We assume that experience and contacts acquired in the running of one fund carry over to the firm's next fund and so measure VC experience at the parent firm rather than the fund level. We aggregate round-by-round investments in portfolio companies to calculate fund-specific variables. We exclude all funds that are not independent (structured as limited partnerships with overlapping sequences of funds), since corporate and banking VCs often have strategic goals that lead then to specialize or generalize their portfolios irregardless.

Our data, which is described in some detail in Hochberg, Ljungqvist, and Lu (2007), contains the vast majority of U.S. VC investments made between the years 1975 and 2003. Owing to the VC investment cycle, relatively recent funds have not yet operated for long enough to fully observe the breadth of their investment types and determine the extent to which they are specialized or generalized. To allow our measure of portfolio size and specialization to include the first four years of a fund's life, when investments are made, we exclude all funds raised after 1999.[8] Our results are robust to including funds of later vintages.[9] We further exclude funds raised before 1980, both because the reliability of the Venture Economics data pre-1980 is lower, and because venture capital as an asset class that attracts institutional investors has only existed since 1980.[10]

Extremely small funds may appear to be specialized, even if they do intend to be specialists and are simply choosing the best investment irregardless of industry, or choosing randomly across industries. In order to avoid mechnically inducing a negative correlation between specialization and size, we exclude all funds with fewer than five unique portfolio companies. This

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[8] Closing the sample period at year end 1999 provides at least four years of investment activity for the youngest funds, using November 2003 as the latest date of investment data in our sample.

[9] In future versions, we intend to expand the sample to include data on more recent years.

[10] The institutionalization of the VC industry is commonly dated to three events: The 1978 Employee Retirement Income Security Act (ERISA) whose Prudent Man rule allowed pension funds to invest in higher-risk asset classes; the 1980 Small Business Investment Act which redefined VC fund managers as business development companies rather than investment advisers, so lowering their regulatory burdens; and the 1980 ERISA Safe Harbor regulation which sanctioned limited partnerships which are now the dominant organizational form in the industry.

ensures that if we see a fund whose investments are primarily concentrated in a single industry, it is likely due to intent, rather than chance.

Our final dataset includes 1820 funds managed by 879 VC firms. Table I describes our sample funds. The average sample fund had \$87 million of committed capital, with a range from \$0.1 million to \$5 billion. (Fund size is unavailable for 33 of the 1,820 sample funds.) Fund sequence numbers denote whether a fund is the first, second and so forth fund raised by a particular VC management firm. The average sample fund is a third fund, and the median is a second fund, though sequence numbers are missing in Venture Economics for 258 of the sample funds. 30% of funds are identified as first-time funds.

As our measure of portfolio size, we compute the number of unique portfolio companies in which a given fund invests over the course of its life. The average portfolio for our sample funds consists of approximately 23 unique portfolio companies, while the median fund portfolio consists of 17 unqiue portfolio companies.

To measure specialization, we compute two concentration measures. As a measure of industry specialization, we compute the Herfindahl-Hirschman Index (HHI) of investment by industry for each fund, based on the number of investments made by the fund in each industry. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-technology. As a measure of geographic specialization, we compute the HHI by MSA based on the number of investments made by the fund in each of the 287 Metropolitan Statistical Areas in our dataset. All our reported results are robust to employing HHI computed using dollar investment amounts in each industry or MSA instead of number of portfolio companies. The median fund in our sample has an industry HHI measure of 0.36, with a arnge from 0.18 to 1, and a geography HHI measure of 0.22, with a range of 0.04 to 1.

As in Hochberg, Ljungqvist, and Lu (2007) and Hochberg, Ljungqvist, and Lu (2009), we derive four proxies for the experience of the VC parent firm, in addition to fund sequence number. These measure the age of the VC firm (the number of days since the VC firm's first-ever investment); the number of rounds the firm has participated in; the cumulative total amount it has invested; and the number of portfolio companies it has backed. Each is calculated using data from the VC firm's creation through to the year the fund in question was raised. To illustrate, by the time Sequoia Capital raised Fund IX in 1999, it had been active for 24 years and had participated in 888 rounds investing a total of $1,275 million in 379 separate portfolio companies. In the interest of brevity, we present univariate sorts and regression results using only the cumulative number of days since the VCs first-ever investment, and the cumulative total investment amount, though we obtain similar results using any of the four measures.

As a measure of the tendency to invest in earlier stage deals, which may have a higher probability of failure, we calculate the proportion of deals the fund has invested in that were reported to be at seed or early stage of development at the time the fund first invested in them. We define a seed or early stage dummy variable as taking the value of one if the fund first invested in its portfolio companies at the seed or early stage with greatest frequency. 13.3% of funds are thus defined as primarily investing in seed or early-stage investment opportunities.

To proxy for "money chasing deals," which may lead to the funding of more marginal projects with lower probabilities of success Gompers and Lerner (2000)), we compute the aggregate inflows into VC funds in the year a sample fund was raised. Table I shows that the average fund in our sample was raised ina year in which $23.4 million flowed into the VC industry.

5 Testing the Model's Predictions

5.1 Correlations and Univariate Sorts

5.1.1 Size and Specialization

The main implication of our model is that size and specialization are substitutes. As can be seen in Table II, in our dataset, portfolio size and specialization are indeed significantly negatively correlated unconditionally, on the order of -0.24 to -0.29, depending on the dimension of specialization. Panel A of Table III presents univariate sorts of portfolio size over quartiles of fund specialization, and univariate sorts of our specialization measures across quartiles of fund portfolio size. As can be seen from Panel A, the negative relationship between portfolio size and specialization is striking: regardless of specialization measure, portfolio size declines sharply as we move from the lowest quartile of specialization, where firms are the least specialized (most generalist), to the highest quartile, where firms are the most specialized (least generalist). For example, firms in the bottom quartile of industry specialization (industry HHI by number of companies), the industry generalists, have a mean portfolio size of approximately 30 companies, while firms in the top quartile of industry specialization, the industry specialists, have a mean portfolio size of approximately 17 companies. The magnitudes of the differences between the bottom and top quartiles of specialization for industry specialization calculated by dollar value of investment, and for geographic specialization, are a bit higher, at approximately 16 and 17 portfolio companies difference, respectively, while for stage specialization, the difference in portfolio size between generalists and specialists is slightly lower, at 12 companies. Across all four measures of specialization – industry ($ and #), geography and stage – the differences between portfolio size for the most generalist funds and the most specialist funds is significant at the 1% level.

We find the complementary pattern when we reverse the order of the univariate sorts, and instead sort fund specialization measures across quartiles of portfolio size. Panel B shows that as we move from the lowest quartile of portfolio size to the highest quartile of portfolio size, specialization decreases significantly, regardless of the dimension on which it is measured. Once again, these differences are significant at the 1% level for all four measures of specialization – industry, geography and stage.

5.1.2 Proxies for Skill and Cost of Capital

Our model predicts that higher skill and lower cost of capital should lead to larger portfolios and more generalist firms. As noted in Section 3, measures such as experience and fund sequence number can be interpreted both as proxies for inate VC skill and as proxies for cost of capital, with less experienced funds and lower sequence funds likely facing higher costs of capital due to uncertainty over attribution of performance to skill versus luck. We note that our model does not provide a way to empirically distinguish between the effects of skill or cost of capital. Our prediction, based on the model, is that greater experience (or higher fund sequence number) should be associated with larger, less-specialized portfolios.

As can be seen in Table II, the unconditional correlation between experience and size is indeed positive, regardless of the measure of experience employed. The unconditional correlations between portfolio size and experience range from 0.18 for the measure of experience based on the number of days since the parent firm's first investment, to 0.26 for the experience measure based on the number of portfolio companies the parent has invested in up to the fund's vintage year. As an alternative measure of experience, we can also consider fund sequence number; the higher the sequence number, the longer the fund has managed to survived and the more funds it has successfully raised, suggesting a good track record, and thus higher skill (and/or lower cost of capital). As can be seen from Table II, the unconditional correlation between fund sequence number and portfolio size is also positive and significant, at 0.10.

Panel B of Table III presents univariate sorts of portfolio size and specialization measures over quartiles of fund experience and fund sequence number. (The table employs experience based on number of days since parent firm's first investment, though similar results obtain over the other three experience measures.) As predicted by our model, firms in the highest quartile of experience or fund sequence number are significantly larger than those in the lowest quartile of experience, with the difference in mean portfolio size between the highest and lowest quartiles of experience at approximately 10 firms.[11] Similarly Sorts of specialization over quartiles of fund parent firm experience at vintage or sequence demonstrate that more experienced firms are less specialized than inexperienced firms, with the difference in specialization between the highest and lowest quartiles of firm experience significant at the 1% level for both dimensions of specialization.

5.1.3 Probability of Investment Success

Much as factors that increase the returns to VC activity (such as higher skill and lower cost of capital) should be associated with larger portfolios and less specialization according to our model, factors that decrease the attractiveness of VC investing, such as lower probability of successful outcome, should increase specialization and reduce portfolio size. Earlier stage deals are more speculative, and have a lower probability of success. Gompers and Lerner's (2000) "money chasing deals" results, whereby due to increased competition for a limited number of attractive investment opportunities leads to prices being bid up, and more marginal projects being funded. We therefore employ two measures to proxy for increased probability of failure: an indicator variable taking the value of one if the fund primarily invests in seed or early stage deals, and VC fund inflows in the year the fund was raised.

As can be seen in Table II, the correlation between the early stage indicator and portfolio size is -0.07, while the correlation between the early stage indicator and our measures of specialization is positive, ranging from 0.07 for industry specialization (HHI by # of companies per industry) to 0.20 for geography specialization (HHI by # of companies per MSA). Simi-

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[11] This is also consistent with findings on dollar size of funds and experience documented in Kaplan and Schoar (2005), Gottschalg and Phalippou (2007) and Hochberg, Ljungqvist and Vissing-Jorgensen (2009).

larly, the correlation between inflows and portfolio size is -0.13, and the correlations between inflows and the four measures of specialization are positive, ranging from 0.16 for geography specialization (HHI by # companies)to 0.29 for industry specialization (by # companies). All the reported correlations are statistically significant at the 1% level.

Funds investing primarily in seed or early stage deals exhibit a mean portfolio size of 19.4 companies, versus a mean portfolio size of 23.6 portfolio companies for funds that do not invest primarily in seed or early stage deals; the difference is significant at the 1% level. Early-stage funds also exhibit higher levels of specialization in the raw data. Early-stage funds have mean industry HHIs of 0.42, versus 0.39 for later-stage focused funds, and geography HHIs of 0.37, versus 0.26 for later-stage funds; both these differences are significant at the 1% level.

Panel C of Table III presents univariate sorts of portfolio size and specialization measures over quartiles of total inflows. As predicted by our model, the portfolio size of funds raised in years in which inflows into the VC industry were highest are significantly smaller than the portfolio size of funds raised in years in which inflows into the VC industry were lowest, with the difference in mean portfolio size between the highest and lowest quartiles of inflows approximately 7.25 firms. Similarly, sorts of specialization over quartiles of total demonstrate that funds raised in years in which inflows into the VC industry were highest are significantly more specialized than funds raised in years in which inflows into the VC industry were lowest, with the difference in specialization between the highest and lowest quartiles of firm experience significant at the 1% level for both geography and industry specialization measures.

Both the correlations and the patterns in the univariate sorts are consistent with the predictions of the model. We now turn to analyzing the relationships between our key variables of interest in a multivariate setting.

5.2 Multivariate Models

We present two sets of multivariate models analyzing the relationship between portfolio size, specialization and our proxies for skill, cost of capital, and probability of failure. Our first set of models uses specialization as the dependent variable, while our second set uses portfolio size as the dependent variable. Table IV presents models in which the dependent variable is the industry specialization (HHI) of the fund's portfolio, and the independent variables are the proxies for the variables of interest from our model, described above, as well as year dummies that provide additional controls for changing conditions over the course of our sample. Table V prsents similar models, this time employing geography specialization as the dependent variable. Our specialization measures have support on [0,1], and positive mass on 1. To avoid the resulting well-known biases of OLS in this situation, we estimate fractional logit models using quasi-MLE (see Papke and Wooldridge (1996)). This involves modeling the conditional mean, $E(y|x) = e^x/(1+e^x)$. All models are estimated included year controls (not reported), and standard errors are heteroskedasticity-consistent and clustered by VC parent firm.

In each table, we present five models. In column (1), we present a simple model of specialization as a function of portfolio size. In columns (2) and (3), we model specialization as function of our other independent variables of interest, experience, the indicator for early-stage focus, and VC inflows alone, once using the natural logarithm of days since first startup investment by the parent firm as a measure of experience, and once using the natural logarithm of fund sequence number as our measure of experience[12] In columns (4) and (5), we estimate models with the full range of variables of interest from our model.

In all five of the models estimated, for both dimensions of specialization, we observe a clear, statistically significant negative relationship between portfolio size and specialization. The magnitude of the associated relationship is substantial: holding all other variables at their

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[12] fund sequence number and fund experience are highly correlated, on the order of 0.75, and thus we include them in our empirical models separately, rather than together. Our results are robust to emplying the three other direct measures of experience described above as well.

means, a one standard deviation increase in fund portfolio size is associated with a reduction in industry HHI that ranges from -0.033 to -0.045, depending upon the exact specification estimated. (This compares to the unconditional mean industry HHI of 0.40.) Similarly, holding all other variables at their means, a one standard deviation increase in fund portfolio size is associated with a reduction in geography HHI that ranges from -0.056 to -0.066, depending upon the model estimated (compared to the unconditional mean geography HHI of 0.28).

As our model predicts, the estimates from Tables IV and V indicate that proxies for higher skill or lower cost of capital as associated with less specialization: holding all other variables at their means, a one standard deviation increase in fund parent firm experience (sequence number) is associated with a reduction in industry HHI of approximately -0.021 (-0.022), and a reduction in geography HHI of approximately -0.012 (-0.017), depending on the exact model estimated. Increases in probability of portfolio company failure, proxied for by investment in earlier stage companies or by money chasing deal, are associated, as predicted by the model, with increased specialization of the fund's portfolio. Holding all other variables at their means, focusing on early-stage portfolio companies is associated with an increase of 0.016 to 0.025 in industry specialization of the portfolio, and 0.085 to 0.089 in geography specialization, depending on the model estimated. A one standard deviation increase in total VC inflows into the industry is associated with an increase in industry HHI in the range of 0.037 to 0.050, and an increase in geography HHI of 0.018 to 0.034, depending on the exact model estimated.

In, Table VII, we reverse the designation of dependent variable, and analyze the relationship between the the exogenous variables in our model and portfolio size. We take two appraoches to analyzing portfolio size. In Panel A of the table, the dependent variable is the natural logarithm of portfolio size. In Panel B, to demonstrate robustness when avoiding the known issues related to the estimation of count variables, we estimate poisson models of portfolio size (the count of unique number of portfolio companies). In the first two columns of each panel, we estimate simple models of portfolio size as a function of specialization (industry or geography HHI). In the third column, we model size as a function of the proxies for the exogenous variables in our model. In the fourth and fifth columns, we estimate models of size as a function of industry specialization in addition to our exogenous variables, using two proxies for higher skill and lower cost of capital: our measure of experience based on days the VC parent firm has been operating, and sequence number (both in natural logarithm). In the sixth column we model size as a function of geography specialization and our proxies for exogenous variables.

In both panels, similar patterns emerge. In all five of the models estimated that include one of our specialization measures on the RHS, in either panel, we observe a positive association between specialization and size, consistent with the predictions of our model. We observe a positive association between either proxy for skill and cost of capital and size, and a negative association between our proxies for higher probability of project failure and size consistent with the predictions of the model. Here too, the magnitudes of the effects are large. Holding all other variables at their means, a one standard deviation increase in industry (geography) specialization is associted with a decrease in portfolio size of 4.2 to 5.6 (5.32 to 6.6)companies, depending on the model estimated. This compares to an unconditional mean portfolio size of 23 companies. A one standard deviation increase in experience is associated with an increase in portfolio size of 4.3 to 4.4 companies, a one standard deviation increase in total VC inflows is associated with a decrease in portfolio size of 2.2 to 3.5 companies, and focusing on early stage companies is associated with a decrease in portfolio size of 1.6 to 3.4 companies, depending on the model. With the exception of the coefficients on the indicator for early-stage investment focus in two of the twelve models, all the coefficients are statistically significant at conventional levels, and the vast majority are significant at the 1% level.

Overall, the empirical relationships documented in Tables II through VI appear to be consistent with the main predictions of our model, and very different than the patterns generally presumed in the investments literature with regards to size and scope. These patterns emphasize the importance of accounting for access to deal flow when examining the choice of specialization and size in a setting where deal selection is critical.

That said, we note that our empirical analysis merely documents the nature and sign of the association between the variables of interest, but does not amount to rigorous estimation of the first-order conditions implied by our model. We would ideally like to estimate a set of simlutaneous equations in which specialization and size are jointly determined as a function of each other and other model parameters and with a correlated error structure. In order to estimate such a system, however, we need two instuments, one for size and one for specialization, in order to satisfy the order condition. Our model implies an instrument for portfolio size: both skill and cost of capital (which are not empirically distinguishable in our model) appear only in the first-order condition for size. Thus, skill and cost of capital affect specialization only through portfolio size, and could be used as an instrument for size. In contrast, the model does not provide an equivalent exogenous variable that could be used to instrument for specialization, as all the exogenous variables in our model appear in the first-order condition for specialization. Thus, the model does not allow us to identify and estimate the full system of equations implied by the first order conditions in a simultaneous manner (say, through 3SLS or similar methods).

6 Conclusion

There is a general presumption in economics and finance that specialization enhances productivity and is thus an important driver of value. In the venture capital industry, however, we find that larger and more experienced VC firms tend to be generalists, investing in a wide range of industries, across a wide swath of geographies and across many stages of investments. Size and specialization appear to be complements across all three dimensions. In this paper, we present and test a model of project selection that explains why size and specialization are complements. We also show how positive factors, such as higher skill or lower cost of capital, induce VCs to become larger in portfolio size and scope, and how negative factors, such as higher probabilities of project failure, induce VC portfolios to become smaller and more specialized.

Within the VC context, past literature recognizes four main uses for internal capital markets. First, resources can be re-allocated from a failing project to a successful project. Here, specialization is beneficial in allocation because human capital can re-deployed with smaller value lost if the new activity is closely related to the old activity. Second, internal capital markets can be used to provide sharper incentives to entrepreneurs. If the VC cannot commit to an incentive contract across rounds, which seems likely, then a VC can use capital rationing to create a tournament for follow-on funding. Specialization is beneficial in incentives because the tournament winner is allocated resources from the loser(s). Third, internal capital markets can be use for co-insurance. Since there are financial costs to failure of a given startup investment, multiple projects may allow a VC to continue operating even after some failures. All else equal, weaker firms may then prefer to be generalists so that the success of multiple projects will be less correlated. Fourth, internal capital markets can be used to pick winners – to develop multiple projects and then choose which one to continue. For this to be effective, the VC needs detailed information about each project, and prefers to have any noise in the information to be correlated. All of these abilities imply we should see higher returns for specialists.

Offsetting the beneficial effects of specialization are the mechanics of deal flow. VCs do not generate their own projects. Instead, they match their financial and human capital in development with entrepreneurs who have ideas. Thus, a primary determinant of VC success is the quality of their deal flow. Having access to the most deals - being a generalist - excludes the fewest deals from VC participation and enhances opportunities. Then the basic tradeoff for specialization is that it increases the profitability of any given project that the firm undertakes, but it reduces the set of available projects. When firms create their own projects and have quasi-monopoly power when deciding to improve them, the search for new projects is less important. Conversely, because a VC cannot create projects, but instead must find them in a quasi-competitive market, the ability to examine a wide range of projects is primary. Taking into account both the benefits of internal capital markets and the mechanics of deal flow can therefore provide insights into issues of portfolio size and scope and the relationship between them.

We present a parsimonious model of deal selection and improvement in which a VC firm makes two choices: the size of the firm (number of investments) and the degree of specialization. Specialization improves the payoff to the VC of any given project whether it succeeds or not. The assumed disadvantage to specialization is that a specialist VC cannot evaluate and develop all possible projects.

We test four of the model's main empirical predictions in a large dataset consisting of U.S. Venture capital funds raised over the period 1980 to 1999. Our empirical evidence is consistent with the predictions of the model. Size and specialization appear to be substitutes: larger VCs are less specialized, and more specialized VCs have smaller portfolio size. Factors such as experience, which can be considered a proxy either for higher skill or for lower cost of capital, decrease specialization and are associated with larger portfolio size. Factors such as money chasing deals, or investment in earlier stage projects (with larger inherent ex ante probabilities of failure), which decrease the returns of VC investment, are associated with greater specialization and smaller portfolios.

Our work provides an initial set of insights both into how VC portfolios are structured, and into the frictions that affect the choice of a VC to specialize along a particular dimension or not. The predictions of our model and our empirical implications and findings differ from the findings in the traditional internal capital markets literature, supporting the notion that funding a portfolio of projects in a setting where access, identification, and selection of projects are critical, is very different from funding a portfolio of projects within a firm.

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Table I. Descriptive Statistics

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 (the "vintage years") and make at least five investments over the course of their lives. Fund portfolio size (#) is the number of unique portfolio companies the fund invested in over the course of its life. Fund assets ($) is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the first, second and so forth fund raised by a particular VC management firm. The four measures for the investment experience of a sample fund's parent (management) firm are based on the parent's investment activities measured between the parent's creation and the fund's vintage year. By definition, the experience measures are zero for first-time funds. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the sample fund's vintage year. Specialization measures are derived using the investments made by the sample fund over its lifetime. Industry HHI (#) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the number of unique portfolio companies invested in by the fund in each Venture Economics industry category. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-technology. Industry HHI ($) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the total dollar values invested by the fund in each industry. Geography HHI is the Herfindahl-Hirschman Index of the fund's investments across Metropolitan Statistical Areas (MSAs), using the number of unique portfolio companies invested in by the fund in each of the 287 US MSAs represented in the dataset.

	No.	Mean	Std. dev.	Min	Median	Max
Fund characteristics						
fund portfolio size (# companies)	1820	23.03	19.31	6	17	212
fund assets ($m)	1789	87.33	195.08	0.1	36	5000
sequence number	1562	3.54	3.78	1	2	31
first fund (fraction, %)	1820	29.8				
Fund specialization						
industry HHI (# companies)	1820	0.40	0.15	0.18	0.36	1
industry HHI ($ value)	1819	0.44	0.17	0.17	0.4	1
geography HHI (# companies)	1814	0.28	0.18	0.04	0.22	1
Fund parent's experience (as of vintage year)						
days since parent's first investment	1820	2195.59	2380.06	0	1279	9130
no. of rounds parent has participated in so far	1820	108.32	227.14	0	19	2292
aggregate amount parent has invested so far ($m)	1820	101.16	306.41	0	14.84	6563.61
no. of portfolio companies parent has invested in so far	1820	42.05	70.91	0	13	601
Competition (money chasing deals)						
VC inflows in fund's vintage year ($bn)	1820	23.38	27.87	2.29	75.13	84.63

Table II. Correlations

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 (the "vintage years") and make at least five investments over the course of their lives. Fund portfolio size (#) is the number of unique portfolio companies the fund invested in over the course of its life. Fund assets ($) is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the first, second and so forth fund raised by a particular VC management firm. The four measures for the investment experience of a sample fund's parent (management) firm are based on the parent's investment activities measured between the parent's creation and the fund's vintage year. By definition, the experience measures are zero for first-time funds. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the sample fund's vintage year. Specialization measures are derived using the investments made by the sample fund over its lifetime. Industry HHI (#) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the number of unique portfolio companies invested in by the fund in each Venture Economics industry category. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-technology. Industry HHI ($) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the total dollar values invested by the fund in each industry. Geography HHI is the Herfindahl-Hirschman Index of the fund's investments across Metropolitan Statistical Areas (MSAs), using the number of unique portfolio companies invested in by the fund in each of the 287 US MSAs represented in the dataset. The table presents pair-wise correlations between variables of interest and fund portfolio size and specialization measures. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	fund portfolio size	industry HHI (#)	industry HHI ($)	geography HHI (#)
Fund characteristics				
fund portfolio size (# companies)	1.00	-0.26***	-0.29***	-0.29***
fund assets ($m)	0.31***	0.02	-0.03	-0.10***
sequence number	0.10***	-0.09***	-0.06***	-0.10***
first fund (fraction, %)	-0.01	0.01***	0.07***	0.09***
Fund specialization				
industry HHI (# companies)		1.00	0.81***	0.18***
industry HHI ($ value)			1.00	0.16***
geography HHI (# companies)				1.00
Fund parent's experience (as of vintage year)				
days since parent's first investment	0.18***	-0.09***	-0.09***	-0.11***
no. of rounds parent has participated in so far	0.25***	-0.10***	-0.08***	-0.11***
aggregate amount parent has invested so far ($m)	0.25***	-0.03***	-0.05***	-0.11***
no. of portfolio companies parent has invested in so far	0.26***	-0.10***	-0.09***	-0.12***
Competition (money chasing deals)				
VC inflows in fund's vintage year ($bn)	-0.13***	0.29***	0.22***	0.16***

Table III. Univariate Sorts

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 (the "vintage years") and make at least five investments over the course of their lives. Fund portfolio size (#) is the number of unique portfolio companies the fund invested in over the course of its life. Specialization measures are derived using the investments made by the sample fund over its lifetime. Industry HHI (#) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the number of unique portfolio companies invested in by the fund in each Venture Economics industry category. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-technology. Industry HHI ($) is the Herfindahl-Hirschman Index of the fund's investments across industries, using the total dollar values invested by the fund in each industry. Geography HHI is the Herfindahl-Hirschman Index of the fund's investments across Metropolitan Statistical Areas (MSAs), using the number of unique portfolio companies invested in by the fund in each of the 287 US MSAs represented in the dataset. Panel A presents univariate sorts of specialization by quartile of fund portfolio size and of fund portfolio size by quartile of specialization. Panel B presents univariate sorts of specialization by quartile of fund portfolio size and of fund portfolio size by quartile of specialization. Panel C presents univariate sorts of specialization by quartile of fund portfolio size and of fund portfolio size by quartile of specialization. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Panel A. Size and Specialization

	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Q1-Q4
Portfolio size by quartile of fund specialization					
Fund specialization measure					
industry HHI (# companies)	29.88	25.35	19.61	16.91	12.96***
industry HHI ($ value)	31.88	23.53	19.86	16.01	15.87***
geography HHI (# companies)	34.07	21.20	19.19	16.91	17.15***
Fund specialization by quartile of fund portfolio size					
Fund specialization measure					
industry HHI (# companies)	0.45	0.41	0.39	0.32	0.12***
industry HHI ($ value)	0.51	0.45	0.42	0.35	0.16***
geography HHI (# companies)	0.36	0.29	0.25	0.20	0.16***

Panel B. Size, Specialization and Experience

	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Q1-Q4
Portfolio size by quartile of fund experience					
fund portfolio size (# companies)	17.66	21.35	25.64	27.50	-9.83***
Fund specialization by quartile of fund experience					
Fund specialization measure					
industry HHI (# companies)	0.42	0.41	0.37	0.38	0.03***
industry HHI ($ value)	0.46	0.46	0.41	0.41	0.04***
geography HHI (# companies)	0.31	0.30	0.25	0.25	0.05***

Table III. Univariate Sorts (Continued).

Panel C. Size, Specialization and Money Chasing Deals

	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Q1-Q4
Portfolio size by quartile of $ inflows into VC					
fund portfolio size (# companies)	26.35	25.31	20.80	19.11	7.25***
Fund specialization by quartile of $ inflows into VC					
Fund specialization measure					
industry HHI (# companies)	0.36	0.35	0.42	0.47	-0.12***
industry HHI ($ value)	0.40	0.39	0.46	0.50	-0.10***
geography HHI (# companies)	0.25	0.26	0.28	0.32	-0.08***

Table IV. Industry Specialization

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 and invested in at least five portfolio companies. The dependent variable is Industry HHI (#), the Herfindahl-Hirschman Index of the fund's investments across industries, using the number of unique portfolio companies invested in by the fund in each Venture Economics industry category. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-technology. These dependent variables have support on [0,1] and positive mass at 1. To avoid the resulting well-known biases of OLS in this situation, we estimate fractional logit models using quasi-MLE; see Papke and Wooldridge (1996). This involves modeling the conditional mean $E(y|x)=\exp(x\beta)/(1+\exp(x\beta))$. Independent variables are as described in Table I. Year controls are included but not reported. Intercepts are not shown. Heteroskedasticity-consistent standard errors (clustered on parent VC firm) are shown in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Industry HHI (# companies)				
	1	2	3	4	5
ln fund portfolio size	-0.278***			-0.205***	-0.215***
	0.023			*0.024*	*0.024*
ln days since parent's first investment		-0.093**		-0.064***	
		0.013		*0.013*	
ln fund sequence number			-0.014***		-0.107***
			0.022		*0.020*
=1 if primarily invests in seed or early stage		0.133***	0.092***	0.105**	0.070
		0.050	*0.049*	*0.049*	*0.048*
ln VC inflows in funding year		0.164***	0.182***	0.134***	0.149***
		0.023	*0.025*	*0.022*	*0.022*
No. of observations	1,820	1,678	1,561	1,678	1,561

Table V. Geography Specialization

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 and invested in at least five portfolio companies. The dependent variable is Geography HHI, the Herfindahl-Hirschman Index of the fund's investments across Metropolitan Statistical Areas (MSAs), using the number of unique portfolio companies invested in by the fund in each of the 287 US MSAs represented in the dataset. These dependent variables have support on [0,1] and positive mass at 1. To avoid the resulting well-known biases of OLS in this situation, we estimate fractional logit models using quasi-MLE; see Papke and Wooldridge (1996). This involves modeling the conditional mean $E(y|x)=\exp(x\beta)/(1+\exp(x\beta))$. Independent variables are as described in Table I. Year controls are included but not reported. Intercepts are not shown. Heteroskedasticity-consistent standard errors (clustered on parent VC firm) are shown in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Geography HHI (# companies)				
	1	2	3	4	5
ln fund portfolio size	-0.492***			-0.421***	-0.453***
	0.039			*0.038*	*0.042*
ln days since parent's first investment		-0.101***		-0.044**	
		0.019		*0.018*	
ln fund sequence number			-0.171***		-0.102**
			0.036		*0.033*
=1 if primarily invests in seed or early stage		0.476***	0.450***	0.427***	0.412***
		0.071	*0.077*	*0.049*	*0.073*
ln VC inflows in funding year		0.177**	0.148***	0.119***	0.080***
		0.034	*0.039*	*0.035*	*0.041*
No. of observations	1,814	1,675	1,556	1,675	1,556

Table VI. Portfolio Size

The sample consists of 1820 independent venture capital funds headquartered in the U.S. that were started between 1980 and 1999 and invested in at least five portfolio companies. The dependent variable is the fund's portfolio size. Panel A presents OLS models where the dependent variable is the natural logarithm of the fund's portfolio size (number of unique firms). Panel B presents poisson models where the dependent variable is the fund's portfolio size (count of unique firms). Independent variables are as described in Table I. Year controls are included but not reported. Intercepts are not shown. Heteroskedasticity-consistent standard errors (clustered on parent VC firm) are shown in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Panel A. OLS models	*ln* portfolio size					
	1	2	3	4	5	6
industry HHI (# companies)	-1.296***			-1.012***	-1.014***	
	0.125			*0.136*	*0.134*	
Geography HHI (# companies)		-1.309***				-1.127***
		0.100				*0.104*
ln days since parent's first investment			0.141**	0.119***		0.119***
			0.014	*0.013*		*0.014*
ln fund sequence number					0.121***	
					0.031	
=1 if primarily invests in seed or early stage			-0.141***	-0.109**	-0.088*	-0.028
			0.047	*0.045*	*0.046*	*0.045*
ln VC inflows in funding year			-0.148***	-0.108***	-0.113**	-0.109***
			0.036	*0.035*	*0.045*	*0.036*
R^2	0.08	0.12	0.11	0.16	0.10	0.19
No. of observations	1,820	1,814	1,678	1,678	1,561	1,675

Table VI. Portfolio Size (Continued).

Panel B. Poisson models	portfolio size (count)					
	1	2	3	4	5	6
industry HHI (# companies)	-1.632***			-1.217***	-1.271***	
	0.165			*0.174*	*0.179*	
Geography HHI (# companies)		-1.629***				-1.332***
		0.167				*0.169*
ln days since parent's first investment			0.161**	0.135***		0.137***
			0.020	*0.017*		*0.017*
ln fund sequence number					0.122***	
					0.033	
=1 if primarily invests in seed or early stage			-0.189***	-0.160***	-0.134**	-0.073
			0.056	*0.054*	*0.055*	*0.053*
ln VC inflows in funding year			-0.172***	-0.126***	-0.127***	-0.134***
			0.035	*0.034*	*0.042*	*0.035*
No. of observations	1,820	1,678	1,678	1,678	1,561	1,675