The Interactions Between Portfolio Size and Concentration
An Analysis of the U.S. Venture Capital Market

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Abstract

This study examines how a venture capitalist determines the optimal number of companies in her portfolio of investments. We especially focus our analysis on the relationship between a portfolio’s size and its concentration in a particular sector (industry, geographical, or developmental stage). Our empirical investigation uses a dataset of 2,125 VC funds that made 91,486 investments between 1975 and 2003. We hypothesize, based on a literature review of incentives and agency costs related to portfolio size, that a fund focused on one sector will invest in more companies. This hypothesis draws upon the theory that a concentrated fund benefits from an improved ability to reallocate resources across startups. However, we find the opposite to be the case; portfolio size is significantly negatively related to concentration. We present a model that demonstrates that the constrained deal flow faced by a fund concentrated in a specific sector may negatively impact portfolio size. Finally, we provide evidence in support of this alternate hypothesis by utilizing the concept of a VC firm’s “network position.”
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I. Introduction

Venture capital firms and entrepreneurs enjoy a symbiotic relationship. Venture capital provides the necessary resources for young startups to grow and innovate, while entrepreneurs bring new ideas and technical expertise to the table. However, while these two groups share a common goal, their incentives to achieve that goal do not perfectly align. A venture capitalist’s ideal situation includes investing in a highly successful startup firm without incurring any of the costs of nurturing that firm; an entrepreneur wishes to receive capital from a venture capitalist who will ensure that his business flourishes, while retaining the highest possible share of equity in his company. Venture capitalists provide financing amid mismatched incentives and severe informational asymmetries. Once an entrepreneur raises funds for his startup, he may choose to engage in “wasteful expenditures” with these funds or to “increase risk to undesirable levels.” (Gompers and Lerner 2001) Therefore, after the venture capitalist selects her investments, she must make sure to set incentives such that the entrepreneurs with whom she deals are encouraged to exert effort towards their projects. Contracting on compensation controls and various financing instruments serve as examples of how she might set incentives on an individual level. She might also utilize a portfolio approach.

This paper examines how a venture capitalist determines the size of her fund’s portfolio, based on opposing incentives. We especially concentrate our analysis on the relationship between size and one of the most observable and quantifiable metrics of a portfolio: fund focus in a particular sector (industry, geographical area, or startup developmental stage). As we describe, the level of focus that a fund exhibits has far-reaching impacts for both incentives for the VC to invest as well as incentives for entrepreneurs to exert effort.
Throughout our analysis, we treat fund focus as an exogenous variable. Hochberg *et al.* (2008) consider venture capital firm specialization a “product type” decision; a specialist firm in a given sector accumulates experience over many years so that it can sell itself to entrepreneurs. Thus, a fund whose parent firm is a specialist finds it costly to deviate from the firm’s long-term strategy and invest outside the sector of specialization.

Fulghieri and Sevilir (2009) argue that a venture capitalist faces a complex set of tradeoffs when deciding how large her portfolio should be. On one hand, a larger portfolio gives her bargaining power over entrepreneurs, allowing her to credibly threaten to terminate some projects in favor of others. It also maximizes her ability to reallocate resources from failed startups to other continuing projects. On the other hand, increasing her portfolio size forces her to spread her limited human and financial capital across startups, diluting the quality of each project. Her increased bargaining power hurts entrepreneurs’ incentives to exert effort. One of the key insights we take away from Fulghieri and Sevilir’s paper is that increased focus in a portfolio increases a VC’s ability to reallocate resources across startups, making a larger portfolio more attractive to her.

In this paper, we use Fulghieri and Sevilir’s model as a baseline for our hypothesis, and add an extension in order to confirm the applicability of their conclusions. Using an empirical dataset of 91,486 venture investments (aggregated to include 2,125 funds) in the United States between 1975 and 2003, we test the hypothesis that fund focus leads to a larger optimal portfolio size. Additionally, we test funds that specialize in certain sectors in which resource reallocation is most important in order to determine whether the resource reallocation effect plays a large role in this size-focus relationship. Thirdly, we investigate whether firm industry experience increases
the size of a fund’s portfolio due to a more experienced firm’s improved efficiency in reallocating assets across portfolio companies.

We find that, in contradiction of our first hypothesis, fund focus is significantly negatively related to size. We provide evidence that the additional opportunities funds have to reallocate resources within certain sectors – in particular, the life sciences industry and the early stage sector – mitigate the negative size-focus relationship for funds specializing in these sectors. Also, firm experience has a significant, positive impact on portfolio size until we control for network position (below), suggesting that an experienced firm’s improved efficiency in reallocating assets does not by itself lead the firm to invest in large portfolios.

We propose an alternate hypothesis on the optimal portfolio size, in which the deal flow to which a VC has access helps to determine the VC’s portfolio size. A fund that specializes in a particular sector faces constrained deal flow, in the sense that there is a limited number of high-quality deals in any one sector. A generalist, meanwhile, sees higher total deal flow by choosing investments from multiple sectors. In order to test our alternative hypothesis, we draw on the notion of how “well-networked” a VC firm is among its peers, as studied by Hochberg et al. (2007). We show that a fund managed by a well-networked VC firm chooses to invest in a large portfolio much more willingly than the average fund, supporting the view that higher deal flow leads to larger portfolios. Finally, we suggest several additional explanations for the breakdown of one of our three original hypotheses: that VC firms use portfolio size as a signal, and that fund focus serves to mitigate risk, so that funds do not necessarily need to diversify across a large portfolio in order to manage risk.

The body of literature on venture capital investment concentrates heavily on the relationship and contracting between a venture capitalist and a single entrepreneur. Another,
albeit small, subset of this literature analyzes venture capital portfolio size, and we find only one paper that investigates both portfolio size and focus. Kanniainen and Keuschnigg (2003) present in the first of these papers a model that derives the optimal size of a VC fund’s portfolio, centering their analysis on the fact that as a fund expands, the value of each existing project is diluted. In their model, the venture capitalist’s incentives are always worse in a large portfolio. Cumming (2006) provides an empirical test of the determinants of portfolio size using a dataset of 214 Canadian firms. Bernile et al. (2007) present a model that combines the value dilution effect with the effect that portfolio size has on bargaining power for the VC and entrepreneurs, and test their model using a dataset of 42 non-specialized funds. Lastly, Fulghieri and Sevilir (2009) create a model of portfolio size determination that takes into account the value dilution, bargaining power, and resource reallocation effects, as well as the effect of fund focus.

Our paper adds to this body of literature in the following ways. We perform our empirical tests using a comparatively very large dataset; our final testable dataset includes 2,125 funds, while the largest previous empirical test includes 214 funds. Additionally, we provide empirical evidence supporting a novel hypothesis on the decision process in which a VC engages to determine the size of her portfolio. We produce the first study (of all reviewed) that applies Hochberg et al.’s VC network measures to predict portfolio size, and we provide the first empirical test of the relationship between portfolio size and focus.

Our paper also adds to the body of literature on “internal capital markets,” a term for the behavior of corporate conglomerations when the company allocates capital to different divisions to fund projects. Internal capital markets face many of the same issues as venture capital markets; headquarters’ and divisional managers’ incentives are not completely aligned, and headquarters often seeks to wield its large set of divisions to extract rents from individual
divisional managers. (Scharfstein and Stein, 2000) Gertner et al. (1994) argue that the assets from defaulting projects can be reallocated to other divisions efficiently in an internal capital market but does not touch upon the fact that relatedness of the divisions can significantly increase this reallocation ability, as Fulghieri and Sevilir note. Our paper suggests that a corporation focused in a particular sub-industry or sector may also choose to maintain a small number of projects or divisions, due to the reduced opportunity set of shareholder value-enhancing projects that focus triggers.

Our results highlight an important policy implication. We might wish to spur investment in a certain industry – for example, in clean technology – to arrive at a socially preferred outcome. Not only do we wish to spur investment, however; we wish to increase the individual clean technology investment from a limited number of venture capital firms, because these firms have the best reputations for adding value to projects and nurturing innovation. If we would like these firms to focus further in the clean technology industry, one method might be to increase incentives for clean technology entrepreneurs to exert effort, which would in turn increase the probability of success of the marginal deal for each firm and turn it from a negative-NPV into a positive-NPV potential investment. Hence, we provide one mechanism through which the current subsidization of clean-tech startups might increase innovation in the sector.

We present a literature review of the incentive effects that determine the size of a portfolio in Section II. Next, in the same section, we summarize Fulghieri and Sevilir’s 2-firm model and extend it to three firms with one additional focus parameter, in order to confirm the generality of their results. The section ends with a description of our three hypotheses. In Section III, we present our empirical tests of the above hypotheses and discuss the results. Section IV contains our alternative hypothesis on the size-focus relationship, with an empirical test in
Section V. Our last section, Section VI, includes several additional explanations for our unexpected result regarding the relationship between size and focus in a fund portfolio.
II. Literature Review & Hypotheses

II.1 Venture Capital Incentive and Agency Costs

II.1.a Value Dilution

Venture capital firms provide financing amid mismatched incentives and severe informational asymmetries. In choosing the number of startups to include in her portfolio, a venture capitalist must deal with a principal-agent problem; she must take into account not only her own incentives, but also those of the entrepreneurs with whom she is working. This problem reflects the fact that the realization of payoff from investing in a startup is highly dependent on both VC and entrepreneurial effort. (Fulghieri and Sevilir 2009)

A main driver in determining the number of companies in a venture capital fund’s portfolio is its ability to add value to those companies, in terms of both financial and human capital. Empirical research demonstrates that venture capitalists are able to significantly improve the prospects for their portfolio companies. VC-backed firms produce more and higher-quality patents, and are faster in developing their products and bringing them to market. Researchers conclude that VC portfolio companies perform better even after accounting for selection bias, indicating that venture capital firms do, indeed, add value to their investments. (Kortum and Lerner 2000, Hellmann and Puri 2000)

Venture capital resources, however, are scarce. Once a firm raises capital for one of its funds, it cannot easily augment that capital with resources from another fund; partnership agreements often prevent firm co-investment across funds. (Inderst et al. 2007) Additionally, fund covenants often prevent the addition of human capital, in the form of general partners. (Gompers and Lerner 1996) A model, created by Inderst et al., of capital commitment and
staging of investments implies that these covenants are created to signal to portfolio company entrepreneurs that they must compete for limited resources.

As a result of the scarcity of VC human and financial capital, adding companies to a fund’s portfolio dilutes the quality of advice and resources the fund adds to each of its startups, creating a negative externality for existing portfolio companies. Theoretical models in the body of literature on VC portfolio size account for this value dilution in various ways. Kanniainen and Keuschnigg (2003), Cumming (2006), and Bernile et al. (2007) include an endogenous variable for venture capital effort exerted per project that affects the probability of success of the project. The cost of this effort is increasing in the number of portfolio firms, thus reducing the fund’s incentives to add value to each portfolio firm. In contrast, Fulghieri and Sevilir (2009) treat the maximum payoff from all projects as fixed. In their model, assuming all portfolio projects are successful, the payoff from any one investment declines proportionally as companies are added to the portfolio. For example, consider that a venture capitalist has three projects to choose from. If she invests in one project, the total payoff if that project is successful is $\Delta$. However, if she invests in all three projects, and all three projects are successful, the total payoff is still $\Delta$, with each startup contributing $\Delta/3$. The decline in potential payoff from each startup when the VC invests in all three projects reflects the fact that the value of a project declines when the VC’s resources are diluted. While the mechanics of both of these treatments are different, they both prompt a decline in expected payoff per project as projects are added to a portfolio.

Dilution of venture capital value added as portfolio size increases affects both VC and entrepreneurial incentives. Venture capitalists find it costly to nurture many projects and, thus, must be induced by additional incentives to expand their portfolios. Similarly, the return to effort by entrepreneurs is lower as portfolio size increases, because the expected payoff of each project
declines. If venture capitalists choose a large set of investments, they can expect this effect to lower the expected payoff from each project.

II.1.b Bargaining Power

Bargaining incentives must also be taken into account when a venture capitalist determines her portfolio’s size. These incentives stem from the fact that many venture capital investments are staged; a fund invests some capital in a startup, with the expectation that if the startup performs well, the fund will invest additional capital at a later stage. This practice serves to mitigate risk and informational asymmetry, since the VC can observe the merits of the startup before committing all necessary capital. It also serves another function: a credible threat to startups. Sahlman (1990) writes that “the credible threat to abandon a venture, even when the firm might be economically viable, is the key to the relationship between the entrepreneur and the venture capitalist.” Investing in a large portfolio of projects allows venture capitalists to extract greater rents from entrepreneurs when bargaining on shares of the total payoff. They can threaten to terminate a project at the refinancing stage, and this threat is made even more credible by the fact that when a project is terminated, the assets backing that project can be redeployed to back other projects in the fund’s portfolio. In a larger portfolio, the likelihood of finding a suitable venue for redeployment increases. (Fulghieri and Sevilir 2009. This redeployment effect is augmented by a higher degree of relatedness among companies, which is covered in Section II.1.c). Kanniainen and Keuschnigg (2003) argue that, in contrast to Fulghieri and Sevilir’s view, investing in larger portfolios means that a VC must provide entrepreneurs higher profit shares to make up for VC effort dilution in order to retain high entrepreneurial effort. However, they do not take into account the staging of investments nor the threat of terminating projects. If larger
portfolios do, in fact, result in higher profit shares for venture capital funds at the refinancing stage, this provides an incentive for funds to choose more companies at the investment stage.

Entrepreneurs respond to bargaining incentives in the opposite way, according to Fulghieri and Sevilir (2009). The authors predict that in a large portfolio, competition for resources – or, in other words, a higher likelihood of either termination or resource reallocation to other projects – will stunt *ex ante* entrepreneurial incentives, due to decreased *ex post* bargaining power at the refinancing stage. As mentioned above, the threat of termination forces startups to cede profit share to the VC in the bargaining process. Lower profit share reduces an entrepreneur’s share of his project’s expected payoff, and thus his return to effort. A VC can commit to not exploiting entrepreneurs and withholding resources by taking on a small portfolio, thus giving entrepreneurs a reason to exert more effort. Inderst *et al.* (2007) present a potentially contradictory view of entrepreneurial incentives. While they agree that there is a “bargaining power effect” caused by the investor’s threat of termination in a large portfolio, which reduces incentives to exert effort, higher competition for resources also creates a “competition effect.” This latter effect occurs because, in an environment with scarce resources in which a venture capitalist might have incentives to terminate several projects, there is an additional incremental return to an entrepreneur to performing among the best in the fund’s portfolio, in order to secure continuation of his project. If the bargaining power effect is small enough, the competition effect may dominate and a larger portfolio may actually improve entrepreneurial incentives to exert effort. In light of these two different views, portfolio size has an ambiguous effect on entrepreneurial incentives from a bargaining power standpoint. This lies in contrast to the venture capital bargaining power incentives, which according to relevant literature, increase with portfolio size.
In summary, this section has dealt with the interactions between portfolio size and player incentives. We see that the size affects incentives through two distinct mechanisms (with a third to be discussed in Section II.1.c). First, adding portfolio companies dilutes the value a VC fund can add to each of its companies. Intuitively, this value dilution decreases the potential payoff of each project and, thus, decreases both VC and entrepreneurial incentive to exert effort. Secondly, holding a large portfolio benefits a VC by allowing her to extract greater profit shares from entrepreneurs, assuming that she is able to halt or terminate projects. This effect springs from the fact that dealing with more startups increases the credibility of her threat to cancel projects. Because a greater share of the total payoff goes to the VC, she is more likely to provide effort and resources. We have shown why the opposite effect may not occur with respect to entrepreneurial incentives; while entrepreneurs receive lower profit shares, competition for the VC to continue their projects drives them to signal that their projects are, indeed, valuable. Due to these conflicting effects for both entrepreneurs and venture capitalists, we see that there is no unambiguous trend toward large or small portfolios. It is not surprising that the number of fund portfolio companies in our original dataset ranges from one to 373. However, we can draw conclusions regarding the effect of several of the parameters mentioned here. For instance, we might expect that a stronger value dilution effect results in smaller portfolios.

II.1.c Resource Reallocation

Of all literature reviewed, only one paper posits a relationship between the size of a fund’s portfolio and its concentration. This relationship, according to Fulghieri and Sevilir (2009), hinges upon the degree to which resources can be reallocated across startups. One might ask on which characteristic of startups we base our concentration measure. In this paper, we
study the effects of industry concentration, geographic concentration, and concentration in the developmental stage of investments. Concentration in any of these metrics provides the potential for resource reallocation. For instance, biotechnology startups may tend to purchase similar assets to produce different products. In case one of the startups is liquidated, the investor can redeploy these assets to another biotechnology startup. The VC fund can also redeploy its human capital, for which it has absorbed the cost of acquiring biotechnology-specific skills. Gompers et al. (2008) show that firms with a high degree of industry-specific experience react to investment opportunities in that industry more quickly than firms with more diversified experience; this finding points to the difficulty of redeploying human and financial capital across sectors.

As described in Section II.1.b, the threat of terminating a project plays a large role in determining how profit is shared between the venture capital fund and the entrepreneur. Having a more focused portfolio with greater potential for resource reallocation makes this threat even more credible, since it gives the venture capitalist the chance to recoup her losses from value dilution due to initially investing in a large portfolio.

Consider a VC who has invested in two companies, $C_1$ and $C_2$. Both projects will succeed if continued; if both are continued, each will yield a payoff of $\Delta$. However, the VC has already agreed to refinance $C_1$ and to give the entrepreneur $E_1$ who started $C_1$ half of the payoff from the project. She must now bargain with $E_2$. She realizes that, if she drops $E_2$’s project, she will necessarily gain 0. Thus, she prefers any positive share of the project’s payoff, despite the sunk cost incurred when she invested initially.

Now, assume that the companies $C_1$ and $C_2$ are both highly related. If the VC drops $C_2$ out of the portfolio, she can reallocate the assets to $C_1$ such that the payoff to $C_1$ becomes $\Delta + \phi\Delta$, where $\phi$ is the degree of relatedness and is between 0 and 1. The VC’s total payoff becomes
in the event of termination of \(C_2\). \(E_2\) must therefore offer a share, \(x\), of the payoff to the VC high enough to convince the VC to continue the relationship; \(x\) must satisfy the condition, \(\Delta/2 + x\Delta > (\Delta + \phi\Delta)/2\), or in a simpler form, \(x > \phi/2\). In other words, the VC’s payoff from continuing both projects must be higher than that from continuing only one. As we can see, the share ceded to the VC is increasing in \(\phi\). While this example is oversimplified, it provides an intuitive explanation for why resource reallocation increases the bargaining power of the VC.

In larger portfolios, the potential for reallocation of assets is higher, since the VC can distribute the assets to multiple companies and benefits from a higher probability of putting the assets to use. This principle explains the third mechanism for the interaction between portfolio size and player incentives. Venture capitalists face incentives to invest in more companies in the presence of resource reallocation potential. Reallocation serves two purposes; it increases bargaining power due to a more credible threat of termination, and it also mitigates risk of startup failure. VC funds that are efficient in resource allocation can put the assets from failed startups to use. At one extreme, a VC who can redeploy all assets from a failed startup is indifferent to the failures of all but one portfolio company.

A higher degree of reallocation has opposing effects on entrepreneurial incentives. While the VC can more easily exploit entrepreneurs by terminating their startups, thereby reducing \textit{ex ante} entrepreneurial incentives to exert effort, those startups that do remain in the portfolio enjoy higher total payoffs. Fulghieri and Sevilir (2009) claim that the latter effect dominates the first effect. If they are correct, a the efficiency from a higher potential for resource reallocation results in unambiguously positive effects on all players’ incentives.

The positive effects of resource reallocation on player incentives lead Fulghieri and Sevilir to conclude that, in the presence of portfolio companies with high degrees of relatedness,
we should observe larger portfolios. In other words, VC funds that invest mostly in any one industry, geographic market, or developmental stage should choose to invest in a relatively large number of startups. Furthermore, investing in a large portfolio may only be financially feasible for a VC if she can sufficiently reallocate resources and generate synergies across startups. We solidify these effects in Section II.2.

II.1.d Venture Capital Firm Quality

We briefly mention in Section II.1.c the role that a VC firm’s industry experience plays in its ability to redeploy resources. More generally, the quality of a venture capital firm impacts the VC fund’s investment decisions in two major ways. The first is that a “better” venture capitalist can add more value to projects, increasing the total payoff to a project. Secondly, a better VC can reallocate resources more efficiently across startups in the event of startup failure. Gompers et al. (2008) find that in the face of a shock in the number of investments available in a particular industry, firms with a high degree of experience in that industry react by increasing their frequency of investment in the industry. The sensitivity of their investment frequency to investment opportunity set changes in an industry is much higher than that of firms with generalized or little experience. Furthermore, firms with generalized experience react more quickly to changes in the investment opportunity set than young firms with little experience. Gompers et al. argue that the channel through which these differences occur is human capital. That is, focused firms can redeploy their human capital much more easily to other startups in the same industry than to startups in different sectors. We explore the implications of a higher-quality VC investor in Section II.3.
II.2 Fulghieri & Sevilir Model of Portfolio Size and Model Extension

Our hypothesis on venture capitalist decisions relating to portfolio size must take into account the incentives and agency costs reviewed. Specifically, our hypothesis should explore the influence that bargaining incentives, value dilution, resource reallocation, and VC firm quality exert on portfolio size. We choose as our baseline a theoretical model created by Fulghieri and Sevilir (2009); we select this model because, out of all literature reviewed, these two authors are the only ones who examine the effects of fund focus on size. As one of the most important metrics that venture capitalists decide in their portfolio formation strategy, fund focus is also highly measurable, allowing for a testable hypothesis. As we have noted in our discussion on incentives, the focus of a fund also plays a large role in player incentives.

We outline the Fulghieri and Sevilir (henceforth F&S) model in this section to inform the reader on the reasons for performing the analysis presented in this paper. Additionally, to their model, we add several insights that attempt to overcome what we find to be limitations. Namely, we extend the two-startup investment opportunity set to three startups, and add an additional parameter to model the higher degree of resource reallocation in a larger portfolio.

II.2.a Introduction

In the F&S model, venture capitalists and entrepreneurs are risk-neutral. While VCs do make decisions that mitigate risk, the channel through which these decisions are made is the expected payoff, not the standard deviation of potential returns. The success of each of the two identical available startups relies heavily on both venture capital value added and entrepreneurial effort. Additionally, the total value added of a VC is fixed; the venture capitalist cannot expend resources quickly enough to expand its ability to nurture its investments. The idea of limited VC
resources leads to a fixed maximum total payoff, $2\Delta$. Along a similar vein, the VC incurs a fixed cost, $c > 0$, of investment, independent of the number of startups she elects to take on. This cost represents the efforts expended in order to acquire the skills and human capital necessary to advise her portfolio companies. She can choose to spread these assets across startups, or concentrate them on one.

The investment timeline is as follows. The model allows for four dates (no discounting). The VC makes her portfolio decision at time $t=0$. At $t=1$, the VC makes the investment(s) and the entrepreneur(s) exert a level of effort, $p_i$. At $t=2$, the VC observes whether each startup’s business is sustainable (state S) or a failure (F). She decides whether to continue each successful startup and bargains on the share of total payoff given to entrepreneurs. Finally, at $t=3$, the VC and entrepreneur(s) realize their total payoff.

F&S normalize the payoff of overlooked or discontinued projects to 0. That is, if the VC decides against participating in both projects, she receives a 0 payoff. For any project that fails between stage 1 and 2, or for successful projects that are nonetheless discontinued by the VC, the entrepreneur receives a 0 payoff.

The fixed supply of VC resources forces a fixed total payoff. Thus, if the VC invests in one startup, the total payoff is $2\Delta$ if that project is successful. If she invests in two startups, both are successful (state SS), and she continues both, each project produces a payoff of $\Delta$, or half the maximum total. The success of each project is probabilistically determined by the endogenous amount of effort, $p_i$, the entrepreneur decides to exert. This variable is, in turn, determined through the other parameters, including the entrepreneur’s cost of effort, $kp_i^2/2$, where $k > 1$, and the total value added by the VC (an element of the payoff). As F&S note, the linear payoff
structure in their model removes any effect of what they term “VC’s production technology” –
an advantage of holding a larger portfolio due to efficiency and economies of scale.

One of the key insights of this model is that, if one startup fails or is discontinued (state
SF), the assets and resources from that startup can be reallocated to the successful company. The
payoff to continuing the successful startup then becomes $\Delta + \Delta \phi$, where $\phi$ depends on the degree
to which the venture capital fund can transfer assets between startups, or the “relatedness” of the
two companies. $\phi$ must lie between 0 and 1.

F&S ignore bargaining between the VC and each entrepreneur in the first stages of the
model, because contracts must be renegotiated at $t=2$, after the VC observes the state (S or F) of
each startup. As we have noted in our discussion of resource reallocation in Section II.1.c, the
staging of investments is a very common practice, and each financing round requires a new
contract. F&S also assume in this section of their model that entrepreneurs have no outside
option in the bargaining process. This is not a remote assumption; Bruno and Tyebjee (1983)
find that startups that are denied follow-up financing by a VC investor from a previous round
(whether the round was syndicated or not) face a 74% reduction in their chances of obtaining
outside financing.

Bargaining at $t=2$ plays a vital role in determining the VC’s and entrepreneurs’ shares of
total payoff, and therefore each player’s total expected profit. F&S calculate the payoff shares
according to Shapley Value, a game theory mechanism commonly used to calculate bargaining
equilibria. They justify this mechanism by explaining that “according to the solution concept,
each player obtains the expected value of their marginal contribution to all coalitions that can be
formed with all other players actively engaged in bargaining—players’ payoffs can be obtained
in our model as the outcome of a suitable extensive form bargaining game.” Intuitively, the
Shapley value “reflects the notion that that each player’s payoff depends on his marginal contribution to the total payoff, given what others players can obtain by forming subcoalitions.”

We present the formula for calculating the Shapley value, directly as shown by Fulghieri and Sevilir (2009), since we use this concept in our extension of the model as well. We denote the set of players engaged in the bargaining process as N. We let C be a possible (sub)coalition of players from the set of all players (N) engaged in bargaining – that is, $C \subseteq N$. Let $\Pi_T(C)$ equal the total payoff that can be obtained by the players in C if they cooperate. $\Pi_T(\emptyset) = 0$. The Shapley value for player $i \in N$, $v_i$, is defined by:

$$v_i = \sum_{C \subseteq N - i} \frac{|C|!}{|N|!} (|N| - |C| - 1)! \left[ \Pi_T(C \cup i) - \Pi_T(C) \right]$$

(0)

Note that the Shapley value for player $i$ equals player $i$’s payoff after bargaining, not just her share of the total payoff.

11.2.b Model Part 1: VC Invests in One Startup

If the VC invests in only one startup, her profit is determined by the startup’s probability of success ($p$) multiplied by her profit share ($v_{VC}^1$). The initial cost of investment, $c$, is subtracted from that product. Similarly, the entrepreneur’s payoff is equal to the expected project payoff minus his effort cost. Taking $p$ to equal the endogenous probability of success of the project, and $v_i$ to equal player $i$’s share of the total payoff times the total payoff,

$$\pi^1_V = p v_{VC}^1 - c$$

$$\pi^1_E = p v_E^1 - \frac{p^2 k}{2}$$
The Shapley value can be calculated for each player to simply equal \( \Delta \), or half of the total payoff, using equation (0). The entrepreneur decides his level of effort, \( p^* \), by maximizing \( \pi_E \). It follows that:

\[
p^*_1 = \frac{\Delta}{k}, \quad \pi^*_E = \frac{\Delta^2}{2k}
\]

\[
\pi^*_{VC} = \frac{\Delta^2}{k} - c
\]

II.2.c Model Part 2: VC Invests in 2 Startups

Here, we must acknowledge that there are four unique outcomes at \( t=2 \): 1) state SS, both projects are successful, 2) state SF, 3) state FS (for our purposes, same as state SF since firms are identical), and 4) both projects fail, state FF. In the last case, all players receive a 0 payoff from the projects. Importantly, we must calculate different Shapley values for different states, since in each state we are dealing with a different number of players in the bargaining game. We expect that the equilibrium profit shares will be different when the VC bargains with one entrepreneur from when the VC bargains with two. The Shapley value for the VC for a given state – state SS, for example – is defined as \( v_{VC}^2(SS) \), while entrepreneur i’s is \( v_E^2(SS) \). We show the expected profits for the venture capitalist and entrepreneur 1; entrepreneur 2’s expected profit is symmetric, since the startups are identical. The profit for a player i equals the summation (over all possible states of the world) of the probability of a particular state multiplied by player i’s equilibrium payoff in that state, all minus the cost to player i.

\[
\pi^2_{VC} = p_1 p_2 v_{VC}^2(SS) + p_1 (1 - p_2) v_{VC}^2(SF) + p_2 (1 - p_1) v_{VC}^2(SF) - c
\]
\[ \pi_{E_1}^2 = p_1 p_2 v_{E_1}^2(SS) + p_1 (1 - p_2) v_{E_1}^2(SF) - p_1^2 \frac{k}{2} \]  

(4)

In state SF, the Shapley values can be calculated as follows using the formula defined above (equation (0)). \( N = \{ VC, E_1 \} \). If \( E_1 \) and VC cooperate, the total payoff will be

\[ \Pi_{\tau}^2(VC,E_1) = (1 + \phi)\Delta, \]  

since a percentage of the failed startup’s assets are redeployed to the successful startup. The total payoff for the coalition of just \( \{ VC \} \) or just \( \{ E_1 \} \) is equal to 0, since the generation of a positive payoff requires cooperation between the VC and at least one entrepreneur. F&S calculate that:

\[ v_{VC}^2(SF) = v_{E_1}^2(SF) = \frac{(1 + \phi)\Delta}{2} \]  

(5)

In state SF, the entrepreneur and VC each share half of the total payoff. The payoff is increasing in \( \phi \), indicating that the redeployability of assets in the case of failure benefits both the VC and the existing startup.

In order to calculate the Shapley values for state SS, we define \( N = \{ VC, E_1, E_2 \} \). The total payoff from all players cooperating is \( \Pi_{\tau}^2(V,E_1,E_2) = 2\Delta \). The total payoff from cooperation between one startup and the VC is, again, \( \Pi_{\tau}^2(VC,E_1) = (1 + \phi)\Delta \). We see that:

\[ v_{VC}^2(SS) = \frac{2 \Pi_{\tau}^2(V,E_1,E_2) + 2 \Pi_{\tau}^2(V,E_1)}{6} = 2\Delta \frac{3 + \phi}{6} \]  

(6)

\[ v_{E_1}^2(SS) = \frac{2 \left[ \Pi_{\tau}^2(V,E_1,E_2) - \Pi_{\tau}^2(V,E_2) \right] + \Pi_{\tau}^2(V,E_1)}{6} = \Delta \frac{3 - \phi}{6} \]  

(7)

Here, the VC enjoys a share of the total payoff slightly greater than 1/2. Her share is increasing in focus (\( \phi \)), while the entrepreneur’s share is decreasing in focus. The threat to terminate a successful project and to redeploy assets gives the VC added bargaining power.
Substituting E₁’s Shapley value equations (5) and (7) into the equation for entrepreneur 1’s expected profit (4), taking the derivative with respect to p₁ to obtain the first-order condition, and setting p₁=p₂ in equilibrium, F&S calculate that:

\[
p^{2*} = \frac{3(1 + \phi)\Delta}{2(2\phi\Delta + 3k)}
\]

\[
\pi^2_{VC} = \frac{3(\phi\Delta + 3k)(1 + \phi)^2 \Delta^2}{2(2\phi\Delta + 3k)^2} - c
\]

We see that the level of effort (p) is increasing in focus (φ). While on one hand, increased focus forces the entrepreneur to cede profit share to the VC, it also raises the expected payoff for a continued project. Here, the latter effect dominates.

One result of this model is that p¹⁺ > p²⁺, in all cases. Entrepreneurs have greater incentives to exert effort when the VC invests in one startup versus two. This makes intuitive sense, since the payoff to each project is much lower in the larger portfolio. The difference, p¹⁺ - p²⁺, is increasing in Δ; in the larger portfolio, entrepreneurs do not respond as much to changes in payoff because the VC extracts a larger share of that payoff. The difference is lower for larger degrees of relatedness, which serve to increase p²⁺. Lastly, an increase in the cost of effort (k) tends to reduce effort more in the smaller portfolio.

The main conclusions from the model can be summarized as follows:

1) If Δ is low enough, it prevents the VC from investing at all

2) If Δ is very high, the VC invests in only one startup; at high payoff levels, expanding a portfolio is costlier with regard to entrepreneurial effort (p¹⁺ - p²⁺ is increasing in Δ).

In other words, entrepreneurial effort is more necessary to the VC as payoff increases.

3) For “moderate” payoff and high focus, the VC choose two startups
4) The range of “moderate” payoffs for which the VC chooses a larger portfolio becomes wider as focus ($\phi$) increases

II.2.d Model Extension: VC Invests in 3 Startups

F&S’s model faces several limitations. First, the VC investor can only choose between investing in one and two startups. This choice creates a dichotomy; either she benefits from resource reallocation efficiency, or she does not. Secondly, a two-startup model cannot account for an increase in reallocation efficiency as the fund chooses to invest in a larger number of companies. In order to examine Fulghieri and Sevilir’s conclusions in the context of a larger investment opportunity set, we apply their analysis technique to a VC facing the choice to invest in one, two, or three firms. Also, we introduce a new parameter, $\phi_2$, strictly greater than $\phi$, that represents the augmented ability to redeploy assets in a larger portfolio. The reasoning for the new parameter is that in a larger portfolio, when a startup fails, there is a higher chance of the VC finding a match for the human capital and resources from the failed startup. She can then redeploy her assets more efficiently. The VC may also face diminishing marginal returns to resource reallocation. If she must reallocate multiple startups’ resources, she may not be able to do so with the same efficiency across all failed startups.

We modify F&S’s model in the following way. If the VC invests in three startups and one fails or is terminated, we define the resulting resource reallocation such that the failed startup’s potential payoff is recovered by a factor of $\phi_2$ and distributed equally (or with equal probability) to the two remaining startups. If the VC invests in three startups and two of them fail or are terminated, the VC can reallocate assets from one of the startups by a factor of $\phi_2$, and assets from the other startup by a factor of $\phi$. The intuition behind this is that in the case of two
failed startups, the VC is likely to be able to more efficiently match the remaining company with some of the failed startups’ assets, but not all of the assets. There may be decreasing marginal returns to reallocation of assets, so that the second firm’s assets are not as redeployable.

Therefore, if the maximum total payoff in state SSS remains $2\Delta$, the total payoff in state SSF becomes $2(2\Delta/3) + 2\Delta\phi_2/3$. The total payoff in state SFF becomes $2\Delta/3 + 2\Delta\phi_3/3 + 2\Delta\phi_1/3$.

While the algebraic complexity of our results in this section prevents completing some of our analysis using comparative statics, we show numerically that many of F&S’s results still hold in this model extension.

We begin by defining profit functions for the VC and Entrepreneur 1 (the model dictates that Entrepreneurs 2 and 3 have symmetric functions to Entrepreneur 1).

\[
\pi^3_{vc} = p_1p_2p_3v^3_{vc}(SSS) + p_1p_2(1-p_3)v^3_{vc}(SSF) + p_1p_3(1-p_2)v^3_{vc}(SSF) + p_2p_3(1-p_1)v^3_{vc}(SSF) + p_1(1-p_2)(1-p_3)v^3_{vc}(SFF) - c
\]

\[
\pi^3_{e1} = p_1p_2p_3v^3_{e1}(SSS) + p_1p_2(1-p_3)v^3_{e1}(SSF) + p_1p_3(1-p_2)v^3_{e1}(SSF) + p_1(1-p_2)(1-p_3)v^3_{e1}(SFF) - \frac{k}{2} p_i^2
\]

Note that as an example, $v^3_{vc}(SSS)$ represents the Shapley value for the venture capitalist in the SSS state, and the profit equations contain Shapley values for each possible state of the world. We recall that the profit equation for player i equals the summation (over all possible states of the world) of the probability of a particular state multiplied by player i’s equilibrium payoff in that state, all minus the cost to that player. We recall also that the Shapley value for player i represents that player’s payoff after bargaining (in other words, her share of the total payoff multiplied by the total payoff).

We must find Shapley values for the VC and Entrepreneur 1 in three different states (SSS, SSF, SFF), because each of these states involves a different number of bargaining players.
We begin with the simplest state, SFF, where $N$ includes only two players, $\{VC, E_1\}$.

$\Pi^3_I(VC, E_i) = \left(\frac{2}{3} + 2\phi / 3 + 2\phi_2 / 3\right) \Delta$, accounting for the fact that in the presence of value dilution and without resource reallocation, each project contributes a third of the maximum total payoff available, or $2\Delta/3$. However, if two startups fail, resources are reallocated from one startup with efficiency $\phi$, while resources are reallocated from the other with efficiency $\phi_2$.

Shapley values for state SFF are:

\[
v_{VC}^3(SFF) = \frac{\Pi^3_T(VC, E_1) - \Pi^3_T(E_1)}{2} = \frac{2\Delta}{6}(\phi + \phi_2 + 1)
\]

\[
v_{E_1}^3(SFF) = \frac{\Pi^3_T(VC, E_1) - \Pi^3_T(VC)}{2} = \frac{2\Delta}{6}(\phi + \phi_2 + 1)
\]

In this 2-player game, the VC and entrepreneur each receive half of the total payoff, a result we also see in the one-startup and two-startup cases. Their payoffs are both increasing in the reallocation efficiency parameters, $\phi$ and $\phi_2$.

We employ similar logic to obtain the bargaining payoffs in state (SSF). In addition to previously calculated coalition profits, we know that $\Pi^3_T(VC, E_1, E_2) = \left[2 \left(\frac{2}{3} + 2\phi_2 / 3\right)\right] \Delta$, since the one failed startup’s assets are reallocated at the higher efficiency rate, $\phi_2$. It follows that:

\[
v_{VC}^3(SSF) = \frac{2[\Pi^3_T(VC, E_1, E_2) - \Pi^3_T(E_1, E_2)] + 2[\Pi^3_T(VC, E_1) - \Pi^3_T(E_1)]}{6} = \frac{2\Delta}{6}(\frac{2\phi + 4\phi_2 + 2}{3})
\]

\[
v_{E_1}^3(SSF) = \frac{2[\Pi^3_T(VC, E_1, E_2) - \Pi^3_T(VC, E_2)] + \Pi^3_T(VC, E_1)}{6} = \frac{2\Delta}{6}(\frac{-\phi + \phi_2 + 1}{3})
\]

We can see that the VC’s payoff is increasing in the levels of focus; however, surprisingly, the entrepreneur’s share of the payoff is decreasing in $\phi$ and *increasing* in $\phi_2$. This is because $\phi_2$
only affects the reallocation of assets of the first failed firm; the VC cannot use the higher $\phi_2$ as a
bargaining chip to threaten to terminate one of the remaining successful projects. Both successful
projects enjoy the reallocation benefits from the assets of the failed firm.

Lastly, we calculate the Shapley values in the state SSS, using the fact that

$$\Pi_t^3(VC, E_1, E_2, E_3) = 2\Delta.$$ That is, if all startups are successful at $t=2$, the full payoff potential is
realized.

$$v_{VC}^3(\text{SSS}) = \frac{6\Pi_t^3(VC, E_1, E_2, E_3) + 6\Pi_t^3(VC, E_i, E_j) + 6\Pi_t^3(VC, E_i)}{24}$$

$$v_{VC}^3(\text{SSS}) = 2\Delta \frac{\phi/2 + \phi_2 + 3}{6} \quad (16)$$

$$v_{E1}^3(\text{SSS}) = \frac{6[\Pi_t^3(VC, E_1, E_2, E_3) - \Pi_t^3(VC, E_i, E_j)] + 4[\Pi_t^3(VC, E_i, E_j) - \Pi_t^3(VC, E_i)] + 2\Pi_t^3(VC, E_i)}{24}$$

$$v_{E1}^3(\text{SSS}) = 2\Delta \frac{(-\phi/6 - 2\phi_2/6 + 1)}{6} \quad (17)$$

As expected, the VC’s payoff is increasing in both measures of focus, while the entrepreneur’s
payoff is decreasing in both, since the VC uses the threat of project termination to gain
bargaining power. The VC receives over half of the total payoff.

We substitute the entrepreneur’s Shapley value in each of the three states ((13), (15),
(17)) into $\pi_{E1}^3$ (11) to obtain Entrepreneur 1’s expected profit.

$$\pi_{E1}^3 = 2\Delta p_1 p_2 p_3 \left(\frac{-\phi}{6} - \frac{2\phi_2}{6} + 1\right) + 2\Delta p_1 p_2 (1 - p_3) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) + 2\Delta p_1 p_3(1 - p_2) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) + 2\Delta p_1 (1 - p_2) (1 - p_3) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) - \frac{k}{2} p_1^2$$

$$\pi_{E1}^3 = 2\Delta p_1 p_2 p_3 \left(\frac{-\phi}{6} - \frac{2\phi_2}{6} + 1\right) + 2\Delta p_1 p_2 (1 - p_3) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) + 2\Delta p_1 p_3(1 - p_2) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) + 2\Delta p_1 (1 - p_2) (1 - p_3) \left(\frac{-\phi}{3} + \frac{\phi_3}{3} + 1\right) - \frac{k}{2} p_1^2$$

(18)
The first order condition of equation (18) is:

$$p_1(p_2, p_3) = \Delta \left[ \frac{6 - (8\phi + 4\phi_2)(p_2 + p_3) + 9p_2p_3\phi + 6\phi + 6\phi_2}{18k} \right]$$

(19)

As expected, $p_1$ is always decreasing in the cost of effort. Additionally, $p_1$ is decreasing in $p_2$ and $p_3$. As the other entrepreneurs exert more effort, the likelihood of their success increases. $p_1$ prefers that the other startups fail, because he enjoys the benefits of resource reallocation in that case. Also, in a larger ex post portfolio – that is, in a portfolio with more successful companies – the VC has greater bargaining power due to the threat of termination. $p_1$ is increasing in $\phi_2$ and $\phi$ for small values of $p_2$ and $p_3$, but $p_1$ is decreasing in focus for large values of $p_2$ and $p_3$. This occurs because for small values of the other entrepreneurs’ effort and an increase in focus, there is a large probability that their companies will fail and that Entrepreneur 1 will reap the benefit of a greater degree of resource reallocation. However, if the other entrepreneurs exert high effort and focus increases, the chance of failure becomes low, but Entrepreneur 1 still cedes profit share to the VC. Thus, his incentives to exert effort are reduced.

Since startups 1, 2, and 3 are all identical, we set $p_1 = p_2 = p_3$ in equilibrium. We insert these changes into equation (19) and find that:

$$p_3^* = \frac{8\Delta \phi + 4\Delta \phi_2}{9} + k - \frac{\sqrt{10\Delta^2 \phi^2 + 10\Delta^2 \phi \phi_2 + 144\Delta \phi k + 16\Delta^2 \phi_2^2 + 72\Delta \phi_2 k + 81k^2 - 54\Delta^2 \phi}}{\Delta \phi}$$

(20)

Since $p_1(p_2 = p_3 = p_1)$ from equation (19) presents us with a quadratic equation, we must choose one of two solutions to arrive at $p_3^*$. We rely on the logic that the entrepreneurs’ effort level should increase in the payoff ($\Delta$) and therefore choose the one solution out of the two possible ones that satisfies this condition.
Finally, inserting $p^{3*}$ (20) and all of the VC’s Shapley values into the equation for venture capitalist profit (10) results in an expression too complex to be meaningfully reproduced here. Rather than using calculus to derive comparative statics relationships, we use numerical examples. In all examples, we normalize the initial cost of VC investment, $c$, to 0 so that the VC is always willing to invest in at least one startup.

**Conclusion 1:** For high-payoff projects, the VC always prefers to invest in one startup (assuming the cost of entrepreneurial effort is sufficiently low compared to the payoff). That is,

$$\pi^{1*}_{VC} \geq \max(\pi^{3*}_{VC}, \pi^{2*}_{VC}) \text{ if } \Delta > \Delta_c \text{ and } k < k_c$$

$k_c$ and $\Delta_c$ are critical values obtained from comparing the VC’s profit equations when $n=1, 2,$ and 3. As mentioned in F&S’s model, entrepreneurial effort is more necessary to the VC when payoff is higher. In Table II.1 below, we hold payoff constant and vary the focus measures from low to high. We vary them across a broad range in order to cover all critical regions. We also increase the difference between the two focus measures. In all cases, the VC’s profit from investing in one startup ($n=1$) is highest, and entrepreneurial effort is also highest for $n=1$. This statement echoes F&S’s conclusion from the 2-startup model; the entrepreneurial effort in this case is always higher than if the VC invests in two or three companies. The difference between entrepreneurial effort exerted in the case of one investment and that exerted in the case of multiple investments becomes larger as payoff increases, because the VC can extract less of the additional payoff. Hence, the “bargaining effect” counteracts any benefits from resource reallocation. We cannot say the same for the difference between $n=2$ and $n=3$; the shock to entrepreneurial effort is much smaller here than when moving from $n=1$ to $n=2$, especially for
highly focused startups, and cannot necessarily counteract the resource reallocation effect.

**Conclusion 2:** Entrepreneurial effort is generally lower in a larger portfolio. F&S show that in the 2-startup case, this is necessarily always true. When a VC is faced with three startups, this is usually true when k is sufficiently low relative to payoff. In Table II.2, we show that this relationship holds for a range of focus values. In a large portfolio, the payoff of each project decreases dramatically, and the VC holds more bargaining power for extracting profit share, leading to a reduction in incentives for entrepreneurs to exert effort.

**Table II.1**

<table>
<thead>
<tr>
<th>Payoff</th>
<th>( \phi )</th>
<th>( \phi(2) )</th>
<th>k</th>
<th>Startups: 1</th>
<th>2</th>
<th>3</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>65</td>
<td>0.4</td>
<td>0.6</td>
<td>30</td>
<td>141</td>
<td>71</td>
<td>66</td>
<td>2.17</td>
<td>0.96</td>
<td>0.71</td>
</tr>
<tr>
<td>65</td>
<td>0.1</td>
<td>0.2</td>
<td>30</td>
<td>141</td>
<td>69</td>
<td>53</td>
<td>2.17</td>
<td>1.04</td>
<td>0.72</td>
</tr>
<tr>
<td>65</td>
<td>0.8</td>
<td>0.9</td>
<td>30</td>
<td>141</td>
<td>77</td>
<td>78</td>
<td>2.17</td>
<td>0.90</td>
<td>0.70</td>
</tr>
<tr>
<td>65</td>
<td>0.3</td>
<td>0.7</td>
<td>30</td>
<td>141</td>
<td>70</td>
<td>68</td>
<td>2.17</td>
<td>0.98</td>
<td>0.72</td>
</tr>
</tbody>
</table>

**Conclusion 3:** Consistent with F&S’s results, for moderate payoff, a VC is more likely to invest in a larger portfolio when the degree of focus (\( \phi_2 \) and \( \phi \)) is higher. In fact, the decision to further expand to three startups from two is much more sensitive to \( \phi_2 \) than to \( \phi \), stemming from
the definition that $\phi_2$ is the rate of reallocation of resources on the margin between $n=3$ and $n=2$. It follows that the value of $\phi_2$ plays a large role in determining whether the VC invests in two or three startups. F&S have already proven the first implication (that higher focus leads to portfolio expansion from one startup). Table II.3 shows that, all else equal in a moderate-payoff environment, a high value of $\phi_2$, and a high difference between $\phi_2$ and $\phi$, cause the VC to prefer $n=3$ to $n=2$. The high degree of additional resource reallocation dominates the negative effect on entrepreneurial effort.

**Table II.3**

**Effects of Focus on Size**

<table>
<thead>
<tr>
<th>Payoff</th>
<th>$\phi$</th>
<th>$\phi(2)$</th>
<th>$k$</th>
<th>Startups:</th>
<th>VC Profit</th>
<th>Entrepreneurial Effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.1</td>
<td>0.3</td>
<td>8</td>
<td>1</td>
<td>2.00</td>
<td>1.15 1.12 0.50 0.27 0.21</td>
</tr>
<tr>
<td>4</td>
<td>0.7</td>
<td>0.9</td>
<td>8</td>
<td>2</td>
<td>2.00</td>
<td>2.12 2.58 0.50 0.34 0.30</td>
</tr>
<tr>
<td>4</td>
<td>0.2</td>
<td>0.9</td>
<td>8</td>
<td>3</td>
<td>2.00</td>
<td>1.31 2.05 0.50 0.28 0.27</td>
</tr>
<tr>
<td>4</td>
<td>0.4</td>
<td>0.6</td>
<td>8</td>
<td>3</td>
<td>2.00</td>
<td>1.63 1.84 0.50 0.31 0.26</td>
</tr>
</tbody>
</table>

**Conclusion 4:** A high cost, $k$, to entrepreneurial effort invalidates the general observation that larger portfolios necessarily cause lower effort on the part of entrepreneurs. It also causes VC funds to expand even when payoff is very high. This is because the resulting lower effort causes such a high probability of startup failure that the VC finds her resource reallocation ability most useful here. We see in Table II.4 below that in a situation in which the VC would normally prefer to invest in one startup, a significant increase in cost of entrepreneurial effort leads her to invest in three startups. Additionally, varying the reallocation efficiency parameters so that $\phi_2 - \phi$ is large, we find that entrepreneurial effort is actually higher in the case where $n=3$ than when $n=2$. 
In summary, our model extension demonstrates that Fulghieri and Sevilir’s conclusions are applicable beyond their model, in which the VC can invest in a maximum of two startups. We include a mechanism for value dilution, and we show that the negative “bargaining power effect” that a large portfolio has on entrepreneurial incentives is usually amplified in portfolios larger than two companies. We calculate that high project payoffs stunt the incentives for a VC to expand her portfolio. Investment in high-risk technologies is predicted to be generally done within larger portfolios, since the benefits of resource reallocation are important if these companies fail. Startup risk can also be thought of as reducing $\Delta$, F&S’s proxy for expected project payoff. In addition to augmenting F&S’s predictions, we show that diminishing marginal returns to resource reallocation (through the inclusion of a second focus parameter $\phi_2$) increase the VC’s incentives to expand. The larger the magnitude of these diminishing marginal returns to reallocation, the stronger the VC’s preference is to expand.

<table>
<thead>
<tr>
<th>Payoff</th>
<th>$\phi$</th>
<th>$\phi(2)$</th>
<th>k</th>
<th>Startups:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>0.6</td>
<td>0.7</td>
<td>20</td>
<td></td>
<td>45.00</td>
<td>29.25</td>
<td>28.73</td>
<td>1.50</td>
<td>0.75</td>
<td>0.57</td>
</tr>
<tr>
<td>30</td>
<td>0.6</td>
<td>0.7</td>
<td>180</td>
<td></td>
<td>5.00</td>
<td>5.81</td>
<td>7.30</td>
<td>0.17</td>
<td>0.13</td>
<td>0.11</td>
</tr>
<tr>
<td>30</td>
<td>0.3</td>
<td>0.8</td>
<td>180</td>
<td></td>
<td>5.00</td>
<td>4.02</td>
<td>6.37</td>
<td>0.17</td>
<td>0.10</td>
<td>0.11</td>
</tr>
</tbody>
</table>

*Table II.4*

**Cost of Entrepreneurial Effort**

<table>
<thead>
<tr>
<th>VC Profit</th>
<th>Entrepreneurial Effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>45.00</td>
<td>1.50 0.75 0.57</td>
</tr>
<tr>
<td>5.00</td>
<td>0.17 0.13 0.11</td>
</tr>
<tr>
<td>5.00</td>
<td>0.17 0.10 0.11</td>
</tr>
</tbody>
</table>
II.3 Hypotheses

The incentive-based model of venture capital decision-making presented in the previous section allows us to form several testable hypotheses. Namely:

1) The model makes a clear prediction on the relationship between concentration in a venture capital portfolio and its size. As the focus of a portfolio increases, we expect to see its size increase, since the assets of failed investments can be more easily reallocated to other startups. This relationship should hold especially in an environment with moderate project payoffs. We expect that the average project in a fund with multiple companies has a “moderate” potential payoff, and treat this assumption as trivial. The resource reallocation effect of portfolio focus on incentives tends to outweigh the bargaining effect. If the predicted relationship between focus and size of a portfolio does not hold, this result of the model may not hold, either.

2) We predict that higher VC firm quality results in larger portfolios, on average. A VC firm with more experience (especially industry-specific) and higher ability can reallocate resources and generate synergies across startups more efficiently than a VC firm without experience. An increased ability to redeploy assets from a failed startup to other startups should result in a larger number of portfolio companies in order to take advantage of this ability.

3) Funds that are focused on sectors whose companies tend to carry higher risk or greater complementarities should, on average, exhibit this relationship more strongly than other funds, due to the enhanced ability to reallocate resources.
III. Initial Model: Empirical Results

III.1 Description of the Data: U.S. Venture Capital Investments from 1975-2003

We perform empirical tests of venture capital investment decisions using a raw dataset (collected over several years by the thesis faculty adviser, utilizing the Thomson Financial Venture Economics database as well as manual diligence) of 141,333 venture investments. Each of these observations represents one investment by a fund in a company during a particular round of funding for that company. Therefore, we can say that each investment represents a unique fund-company-round combination. This raw dataset represents what we believe to be the vast majority of venture capital investments during the time period from 1975 to 2003 in the United States. Gompers and Lerner (1999) find that the Venture Economics database alone includes over 90% of all venture investments. The only selection bias inherent in this dataset is that which affects the availability of information on investments. That is, if information on a particular investment could not be found, it was excluded from the dataset. Hochberg et al. (2008) note that venture capital investment information is not easily obtained publicly. We do not consider this a bias-inducing problem, because the correlation of information availability with any of the factors in our tests is likely inconsequential.

We restrict the raw dataset to arrive at our final dataset as follows. We aggregate the investments by fund in order to calculate fund-specific variables, removing any investments whose funds could not be specified. Next, we exclude any venture capital funds whose vintage years (the year in which the fund’s capital was raised, Ljungqvist and Richardson 2003) are after 1999 or before 1975. We exclude funds raised after 1999 because it generally takes funds approximately four years to make their initial investments (Levin 2008). Funds raised before 1975 are removed because we only have data on a subset of these funds’ investments. Next, we
remove any venture capital funds that invest in less than six portfolio companies. It is most likely that factors other than the ones we examine (such as internal mandates or the ability to raise funds) have influenced the sizes of these funds’ portfolios. Finally, we exclude any funds for which we cannot calculate the variables of interest.

Our final testable dataset contains 2,125 funds based in the United States. These funds are controlled by 1,080 parent venture capital firms. They made 91,486 investments (unique fund-round-company combinations) during the period from 1975 to 2003. The breakdown of these investments by industry and stage is presented in Section III.3.
III.2 Description of Variables

Aggregated Fund-Level Variables

Fund_Companies
The number of companies in which a venture capital fund invests throughout its life. The VC fund may have invested in its portfolio companies in multiple financing rounds.

HHI_Industry
We use the Herfindahl-Hirschman Index\(^1\) to represent concentration by industry. The percentage of investment in a certain industry is defined as the number of companies the fund invests in within that industry divided by the total number of the fund’s portfolio companies. Our dataset separates startups into six industries, as characterized by the Venture Economics database.

HHI_Industry_Dollars
An alternative method of calculating industry concentration. Here we calculate the fund’s level of focus based on dollar amount invested in a particular industry, rather than number of companies. We include this variable to check for the robustness of results based on HHI_Industry.

HHI_Geog
We calculate geographic concentration using the HHI, defining a sector as a metropolitan statistical area (MSA) in the United States. (Office of Management and Budget) Our dataset includes 287 MSAs.

HHI_Stage
Here, we calculate a fund’s propensity to focus in a particular startup development stage. The Venture Economics database separates startups into four stages: Seed/Startup, Early Stage, Expansion, and Later Stage.

Fund_AUM
The capital that each fund has available to invest (in millions of dollars).

VC Parent Firm Fixed Effects

Experience_Days
A measure of the firm’s investing experience. The number of days between the firm’s first appearance in our dataset and the January 1 of the vintage year of the fund.

\(^1\) HHI is defined as \( \sum_{i=1}^{N} s_i^2 \), where \( s_i \) equals the percentage of investment in sector \( i \), and \( N \) represents the total number of sectors.
Experience_Dollars: The total dollar amount the firm invested within our dataset prior to the fund’s vintage year.

Experience_Weighted: The total dollar amount the firm invested within each industry in our dataset prior to the fund’s vintage year, weighted by the fund’s investment in each of the industry. (This is not a true fixed effect, since it varies with the fund’s investment behavior, but is based on the firm’s overall experience.)

Experience_Companies: The total number of companies the firm invested in prior to the fund’s vintage year.

Corporate_VC: Binary variable that equals 1 if a firm is a corporate VC firm (generally an investment arm of a much larger company; an example would be Cargill Ventures of the agricultural company Cargill).

Year Fixed Effects

Total_Inflows: Total capital inflows to venture capital in the United States during fund’s vintage year.

Ind_Weighted_Inflows: We calculate a measure of weighted capital inflows using the inflows to each of the six industry sectors and weighting by the dollar amount the fund invests in each sector. (This is not a true fixed effect, since it varies with the fund’s investment behavior, but it is based on a fixed effect.)

L_Ind_Weighted_Inflows: Lagged by one year.

Ind_Weighted_Funds: The number of new funds specializing in each industry, weighted by the dollar amount the fund invested in each sector. (This is not a true fixed effect, since it varies with the fund’s investment behavior, but it is based on a year fixed effect.)

L_Ind_Weighted_Funds: Lagged by one year.

Stage Sector Binary Variables

Seed: One dummy variable for each of the four stage sectors.

Early_Stage: If a firm makes its first investment in over 50% of portfolio companies at a particular stage, the variable equals 1.

Expansion

Later_Stage

Stage_general: Equals one if the fund does not invest in 50% of its portfolio companies in any one stage.
Industry x Time Binary Variables

We include 36 dummy variables that represent whether a fund specializes in a certain sector (6 total) and has a vintage year within a certain time period (6 total). These variables control for boom and bust periods within each industry.
III.3 Summary Statistics

We see from Table III.1 that the average number of companies per fund in our functional dataset is 23, but it ranges from six (the defined minimum) to 300. The average company is almost equally concentrated by industry and stage, while concentration by metropolitan statistical area is lower (which we would expect, given the vast number of MSAs throughout the United States). There are companies in our dataset which invest almost equally across industries or developmental stages.

Table III.1

<table>
<thead>
<tr>
<th>Summary of the Final Dataset</th>
<th>Fund Portfolio Metrics</th>
<th>No. Funds</th>
<th>2,125</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Max</td>
</tr>
<tr>
<td>Fund_Companies</td>
<td>23</td>
<td>17</td>
<td>300</td>
</tr>
<tr>
<td>HHI_Industry</td>
<td>41%</td>
<td>37%</td>
<td>100%</td>
</tr>
<tr>
<td>HHI_Geog</td>
<td>27%</td>
<td>22%</td>
<td>100%</td>
</tr>
<tr>
<td>HHI_Stage</td>
<td>40%</td>
<td>36%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table III.2 (below) describes the dataset as divided into specialists in the six possible industries, as well as non-specialist funds. We show the same for specialists in the four startup developmental stages. We define specialists as funds who hold over half of their portfolio companies in one sector. As a precursor to our empirical analysis, this table shows that generalist funds hold larger portfolios on average.

We see in Chart III.1 that a fund’s decision to specialize on a particular dimension does not have a large influence on its decision to specialize in other ways. There does seem to be a positive relationship, but this relation is extremely weak. In this example, funds that are very geographically focused are not necessarily stage-focused. The same holds true for industry concentration, as well.
### Table III.2

**Summary of the Final Dataset by Industry and Stage**

**Fund Portfolio Metrics**

<table>
<thead>
<tr>
<th>Specialist* in:</th>
<th>Mean:</th>
<th>No. Funds</th>
<th>Fund_Companies</th>
<th>HHI_Industry</th>
<th>HHI_Geog</th>
<th>HHI_Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biotech</td>
<td></td>
<td>49</td>
<td>16</td>
<td>52%</td>
<td>25%</td>
<td>40%</td>
</tr>
<tr>
<td>Comm &amp; Media</td>
<td></td>
<td>97</td>
<td>15</td>
<td>50%</td>
<td>30%</td>
<td>42%</td>
</tr>
<tr>
<td>Computer-Related</td>
<td></td>
<td>728</td>
<td>21</td>
<td>51%</td>
<td>32%</td>
<td>40%</td>
</tr>
<tr>
<td>Medical</td>
<td></td>
<td>96</td>
<td>17</td>
<td>49%</td>
<td>24%</td>
<td>41%</td>
</tr>
<tr>
<td>Non-High Tech</td>
<td></td>
<td>179</td>
<td>19</td>
<td>52%</td>
<td>23%</td>
<td>44%</td>
</tr>
<tr>
<td>Semiconductors</td>
<td></td>
<td>14</td>
<td>9</td>
<td>49%</td>
<td>37%</td>
<td>41%</td>
</tr>
<tr>
<td>Non-Specialist</td>
<td></td>
<td>962</td>
<td>27</td>
<td>28%</td>
<td>24%</td>
<td>38%</td>
</tr>
</tbody>
</table>

**Specialist** in:

<table>
<thead>
<tr>
<th>Specialist** in:</th>
<th>Mean:</th>
<th>No. Funds</th>
<th>Fund_Companies</th>
<th>HHI_Industry</th>
<th>HHI_Geog</th>
<th>HHI_Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seed</td>
<td></td>
<td>105</td>
<td>23</td>
<td>39%</td>
<td>36%</td>
<td>48%</td>
</tr>
<tr>
<td>Early Stage</td>
<td></td>
<td>155</td>
<td>17</td>
<td>46%</td>
<td>36%</td>
<td>49%</td>
</tr>
<tr>
<td>Expansion</td>
<td></td>
<td>564</td>
<td>22</td>
<td>43%</td>
<td>25%</td>
<td>50%</td>
</tr>
<tr>
<td>Later Stage</td>
<td></td>
<td>16</td>
<td>21</td>
<td>39%</td>
<td>35%</td>
<td>48%</td>
</tr>
<tr>
<td>Non-Specialist</td>
<td></td>
<td>1283</td>
<td>24</td>
<td>39%</td>
<td>26%</td>
<td>33%</td>
</tr>
</tbody>
</table>

* 50% or more of fund’s portfolio companies in particular sector
** Stage information is not available for several funds

### Chart III.1

![HHI_Geog vs. HHI_Stage: All Funds](chart.png)

Loosely Positive Relationship
III.4 Initial Econometric Model: How is Portfolio Size Related to Fund Focus and Firm Ability?

In this section, we utilize our dataset to empirically test our first two hypotheses. We test our hypothesis that as a VC fund specializes more in one sector, it also tends to invest in more companies in order to take advantage of its additional opportunities to reallocate resources across startups. We have also predicted that a VC firm’s ability affects the size of its funds’ portfolios, largely through the same mechanism. We treat the number of portfolio companies in each fund as our dependent variable, and examine how its variance is affected by fund focus and firm fixed effects. We include separate tests for portfolio concentration based on the three different metrics: concentration by industry, geography, and stage. As a proxy for firm quality, we test for the effect that firm experience has on portfolio size. In Section III.2, we describe several different measures that we construct around firm experience; we only include the most significantly related one here. As noted, Experience_Weighted is not a true fixed effect because its weighting depends on fund behavior, not solely on firm experience. Corporate_VC is included in firm fixed effects, because a corporate VC may be able to generate synergies and higher reallocation across its startups due to its industry expertise. It is necessary to control for year fixed effects as well, since higher venture capital activity in a given year can affect the decision-making process and sentiments toward expanding. We have described our variables for year fixed effects, namely capital inflows in a particular year per industry weighted by the fund’s investment in each industry, and also the number of new VC funds specializing in a given industry weighted in a similar fashion (again, not true fixed effects because they depend on fund investment behavior in addition to the year fixed effects). We test whether lagged values of these have stronger effects; a VC may consider venture capital activity in a previous year and base his current behavior on
what he observes. We include stage dummy variables to proxy for a fund’s risk level, in the absence of detailed data on investment risk and returns. A fund that specializes in seed or early stage investments, for instance, generally invests in riskier companies (Hochberg et al. 2007). These companies’ products or businesses are not yet fully developed, and venture capitalists have not had as much time to assess their probabilities of success as they have had with later stage companies. We include time*industry binary variables to control for boom and bust cycles in various industries. Finally, we control for the assets under management of a fund, because a fund with greater capital available has much higher incentives to choose a larger portfolio. We visualize the model as follows:

\[
\text{Fund}_{\text{Companies}} = \beta_1 \text{Concentration}_{ijk} + [\beta_2 \ldots \beta_3] \text{Stage}_{\text{dummies}}_{ijk} + \\
\beta_6 \text{Fund}_{\text{AUM}} + [\beta_7 \ldots \beta_{41}] \text{Industry} \times \text{Time}_{\text{Dummies}}_{ijk} + \\
\alpha_1 \text{Experience}_i + \alpha_2 \text{Capital}_{\text{Inflows}}_k + \alpha_3 \text{Corporate}_{\text{VC}}_j
\]

Our parameter estimates for this model, as generated in Stata, are presented in Table III.3. We calculate robust standard errors in order to account for heteroskedasticity in our regression. The variance of the unobservable factors is likely to increase as the number of companies in a fund increases, and Wooldridge (2006) notes that in large sample sizes (ours is over 2,000 funds), it is generally necessary to report only the heteroskedasticity-robust standard errors in cross-sectional applications.
### Table III.3a

Explanation of Fund Portfolio Size for Each Measurement of Concentration
Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-21.72***</td>
<td>-21.69***</td>
<td>-44.49***</td>
</tr>
<tr>
<td></td>
<td>(2.928)</td>
<td>(2.198)</td>
<td>(5.089)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00006530***</td>
<td>0.00005930***</td>
<td>0.00006410***</td>
</tr>
<tr>
<td></td>
<td>(0.00001980)</td>
<td>(0.00001950)</td>
<td>(0.00001910)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>-2.327*</td>
<td>-3.511***</td>
<td>-2.820**</td>
</tr>
<tr>
<td></td>
<td>(1.337)</td>
<td>(1.309)</td>
<td>(1.267)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03505***</td>
<td>0.03326***</td>
<td>0.03498***</td>
</tr>
<tr>
<td></td>
<td>(0.005024)</td>
<td>(0.004759)</td>
<td>(0.005207)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.0003271***</td>
<td>-0.0004693***</td>
<td>-0.0003861***</td>
</tr>
<tr>
<td></td>
<td>(0.0001118)</td>
<td>(0.0001092)</td>
<td>(0.0001088)</td>
</tr>
<tr>
<td>Seed</td>
<td>-1.320</td>
<td>0.4495</td>
<td>4.530***</td>
</tr>
<tr>
<td></td>
<td>(1.598)</td>
<td>(1.572)</td>
<td>(1.672)</td>
</tr>
<tr>
<td>Early_Stage</td>
<td>-4.320***</td>
<td>-3.096***</td>
<td>2.236</td>
</tr>
<tr>
<td></td>
<td>(1.155)</td>
<td>(1.139)</td>
<td>(1.386)</td>
</tr>
<tr>
<td>Expansion</td>
<td>-2.870***</td>
<td>-3.156***</td>
<td>4.160***</td>
</tr>
<tr>
<td></td>
<td>(0.8821)</td>
<td>(0.8687)</td>
<td>(1.181)</td>
</tr>
<tr>
<td>Later_Stage</td>
<td>-12.66***</td>
<td>-11.75***</td>
<td>-6.180***</td>
</tr>
<tr>
<td></td>
<td>(2.043)</td>
<td>(2.381)</td>
<td>(1.945)</td>
</tr>
</tbody>
</table>

R^2: 23.23% 25.64% 25.29%

Stage dummy variables compared to Stage_General

* Significant at 10%  ** Significant at 5%  *** Significant at 1%
Robust standard errors calculated

### Table III.3b

Marginal Effects of Main Variables on Fund Portfolio Size
Standardized Coefficients

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-3.490</td>
<td>-3.906</td>
<td>-5.122</td>
</tr>
<tr>
<td></td>
<td>(0.1607)</td>
<td>(0.1801)</td>
<td>(0.1151)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>2.149</td>
<td>1.953</td>
<td>2.111</td>
</tr>
<tr>
<td></td>
<td>(32,920)</td>
<td>(32,920)</td>
<td>(32,920)</td>
</tr>
</tbody>
</table>

Standardized coefficients computed by multiplying OLS coefficients above with independent variable std. deviations
Numbers in parentheses are independent variable standard deviations
We see from the regression results that, contrary to our hypothesis, fund concentration is highly negatively related to portfolio size, across all three measures. This is especially the case when we regress size on stage focus. Venture capital funds that concentrate in particular startup development stages tend to exhibit smaller portfolios; a one-standard deviation change in stage concentration results in an average drop in portfolio size of more than 5 portfolio companies. As a side note, we calculate concentration variables using two different methods: concentration of investment dollars across sectors, and concentration of portfolio companies across sectors. The latter method produces stronger results for industry, geographic, and stage concentration.

As expected, experience in a VC firm tends to increase the size of its funds’ portfolios. In particular, a fund whose parent firm enjoys a level of experience one standard deviation higher than the average firm invests in two more companies than the average fund. The most explanatory experience variable turns out to be Experience_Weighted. We see that corporate venture capitalists generally exhibit smaller portfolios, which may be a contradiction of our view that corporate VCs are adept at reallocating resources across startups in their industry, or rather may simply be a characteristic of the mandates of corporate venture capital funds.

Our year fixed effects impact portfolio size significantly, with the highest effect coming from the industry-weighted inflows lagged by one year. A higher level of funds coming into the venture capital industry leads VC funds to invest in more companies. As expected, funds with more assets under management invest in significantly more portfolio companies.

Interestingly, we find that the effects on size from specialists in a particular stage change significantly when we control for stage concentration in our regressions. One exception is later stage-focused funds; these funds exhibit smaller portfolios after controlling for all three types of concentration.
III.5 Sector-Specific Model: Do VC Funds Focused in Certain Sectors Face Different Decision Processes?

Our review of incentives and agency costs associated with portfolio expansion (Section II.1) leads us to predict that funds concentrated in high-complementarity or high-risk sectors will tend to exhibit larger portfolios. If we can characterize a sector by high complementarity across companies in that sector, those companies are even more highly related to each other than within the average sector. A VC can reallocate resources between the companies, and in the case of failed companies, much more easily. Thus, we expect that higher concentration in such a sector will lead to an even larger portfolio. If a fund invests in high-risk companies, the ability to reallocate resources in case of failed startups come tends to come to the forefront of the decision-making process. We expect that funds investing in high-risk sectors will invest in more companies.

Cummings (2006) writes that there is a higher level of complementarity among entrepreneurial companies in the life sciences industry. Hochberg et al. (2007) tell us that funds that specialize in seed or early stage companies generally invest in riskier companies. We use funds specializing in these two sectors to test whether our predicted size-focus relationship holds more strongly than in the dataset as a whole. We test the same variables that we examine for the entire dataset on these two subsets of the data. We define life sciences-focused VC funds as those that specialize (hold greater than 50% of their portfolio companies) in either biotechnology or the medical industry. Similarly, we define overall early-stage funds as those for whom the majority of portfolio companies are in the seed stage or early stage. Our results are presented in Tables III.4 and III.5.
### Table III.4a

Explanation of Fund Portfolio Size for Each Measurement of Concentration

<table>
<thead>
<tr>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-8.434 (6.770)</td>
<td>-18.42** (7.136)</td>
<td>-20.20*** (6.783)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00009720***</td>
<td>0.00009250*** (0.00003220)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>0.5807 (4.006)</td>
<td>0.3148 (4.115)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.0663*** (0.0180)</td>
<td>0.06108*** (0.01715)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.00004990 (0.0003628)</td>
<td>0.00007260 (0.0003213)</td>
</tr>
</tbody>
</table>

Observations: 145
R^2: 24.75% 28.89% 26.36%

* Significant at 10%  ** Significant at 5%  *** Significant at 1%

Robust standard errors calculated

### Table III.4b

Marginal Effects of Main Variables on Fund Portfolio Size

<table>
<thead>
<tr>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.9632 (0.1142)</td>
<td>-2.748 (0.1492)</td>
<td>-2.628 (0.1301)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>2.885 (29,680)</td>
<td>2.745 (29,680)</td>
</tr>
<tr>
<td></td>
<td>2.787 (29,680)</td>
<td></td>
</tr>
</tbody>
</table>

Standardized coefficients computed by multiplying OLS coefficients above with independent variable std. deviations
Numbers in parentheses are independent variable standard deviations
Table III.5a

Explanation of Fund Portfolio Size for Each Measurement of Concentration
Early Stage-Focused Funds: Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-11.59*</td>
<td>-10.78**</td>
<td>-37.56***</td>
</tr>
<tr>
<td></td>
<td>(6.082)</td>
<td>(4.651)</td>
<td>(9.814)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00002850</td>
<td>0.00005340*</td>
<td>0.00004400</td>
</tr>
<tr>
<td></td>
<td>(0.00003390)</td>
<td>(0.00003020)</td>
<td>(0.00003340)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>-10.50*</td>
<td>-10.88***</td>
<td>-5.089</td>
</tr>
<tr>
<td></td>
<td>(5.219)</td>
<td>(3.953)</td>
<td>(4.890)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.06907***</td>
<td>0.06374***</td>
<td>0.06662***</td>
</tr>
<tr>
<td></td>
<td>(0.01159)</td>
<td>(0.01097)</td>
<td>(0.01134)</td>
</tr>
<tr>
<td>L_IND_Weighted Inflows</td>
<td>-0.0003953*</td>
<td>-0.0005180**</td>
<td>-0.0003547</td>
</tr>
<tr>
<td></td>
<td>(0.0002329)</td>
<td>(0.0002573)</td>
<td>(0.0002460)</td>
</tr>
</tbody>
</table>

Observations: 260
R^2: 33.02% 31.35% 35.44%

* Significant at 10%   ** Significant at 5%   *** Significant at 1%
Robust standard errors calculated

Table III.5b

Marginal Effects of Main Variables on Fund Portfolio Size
Early Stage-Focused Funds: Standardized Coefficients

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-2.117</td>
<td>-2.351</td>
<td>-4.398</td>
</tr>
<tr>
<td></td>
<td>(0.1827)</td>
<td>(0.2181)</td>
<td>(0.1171)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.7399</td>
<td>1.386</td>
<td>1.142</td>
</tr>
<tr>
<td></td>
<td>(25,960)</td>
<td>(25,960)</td>
<td>(25,960)</td>
</tr>
</tbody>
</table>

Standardized coefficients computed by multiplying OLS coefficients above with independent variable std. deviations
Numbers in parentheses are independent variable standard deviations

From looking at III.4a, we ascertain that the highly negative focus-size relationship we find in the entire dataset is smaller and less significant for life sciences-focused funds; it is even insignificant (at the 10% level) when we look at industry concentration as an independent
variable. Note, however, that our sample size in this regression is small; our dataset only includes 145 of these funds. Firm experience and fund assets under management still significantly increase size, while year fixed effects and whether a firm is a corporate VC tend to have no effect for life-sciences focused funds. Additionally, stage dummy variables do not impact fund size here.

Similarly, the fund size-focus relationship is smaller and less significant for early stage firms as seen in III.5a. The notable exception to this occurs when we use stage concentration as an independent variable; this type of concentration decreases portfolio size with a similar magnitude to the same variable used as a regressor in the entire dataset. Firm experience tends to have little effect on size for early stage firms. A corporate VC early stage-focused fund exhibits larger portfolios than non-corporate VCs when we regress on geographic concentration. Finally, fund assets under management have a significant positive effect.
III.6 Discussion of Results

Looking at our results for the dataset as a whole, we can reject our first hypothesis that fund focus leads a VC to choose to invest in a larger portfolio. On the contrary, we observe that larger funds tend to be focused less in any particular sector, whether an industry, stage, or geographic area. We aim to explain in our subsequent sections why this may be the case.

Our empirical results here support (tentatively) our second hypothesis that VC firm quality increases portfolio size, using firm experience as a proxy for quality. We calculate firm experience using a weighted industry experience measure: the dollar amount the parent firm has invested in each industry prior to the fund’s vintage year, weighted by the current fund’s dollar amount invested in each industry. This calculation is consistent with the result in a study by Gompers et al. (2008) that firms with a high level of industry experience react more quickly to shocks in the number of investments in that industry than those with a great deal of generalized experience but low industry experience. They argue that they can redeploy human capital more easily to the same sector. We see in Section V, however, that this is likely not the main driver of the positive relationship between experience and portfolios size.

The stage binary variables, for the most part, exhibit significant effects on portfolio size when compared to non-stage-specialist funds. However, the effect from three out of four of these variables reverses signs when we control for stage concentration in the model. This last result leads us to conclude that much of the negative correlation that stage specialization has with portfolio size is driven by the stage concentration, rather than characteristics of the particular stage sector. We intend for the stage binary variables to proxy for the risk level of a fund, but since there seems to be no coherent ordering of the effect on size by stage specialization, we find that one of the following must be true: either specialization by stage (as we have defined it, with
over 50% of portfolio companies in one stage) does not represent risk well, or risk does not impose a large effect on portfolio size.

Our examination of the fund-focus relationship within two specific specialist groups (life sciences-focused and early-stage focused funds), leads us to believe that there is merit to our hypothesis. Cummings (2006) claims that life science startups are more related to each other than startups in other industries. We test whether specializing in the life sciences sector (145 funds) impacts the relationship between size and focus of a fund, and we find that the negative relationship found in the overall dataset is not as strong and much less significant in life sciences-focused VCs (though the negative effect is certainly still present). We make a similar finding within the subset of early staged-focused funds (260 funds), with the exception that stage concentration retains almost fully its strong negative effect on size. Early stage-focused VCs not only invest in riskier companies, but also enjoy the effects of higher redeployability between companies. Hellmann et al. (2008) claim that the value that VCs need to add to early stage companies is much higher than to later stage companies; VCs who focus on early stage companies must provide their human capital with a specialized skill set that can easily be transferred to other early stage companies. Thus, even if our proxy for risk does not represent risk as intended, we have a second reason to believe that resource reallocation is especially important for early stage-focused funds.

This sector-specific analysis shows us that, for funds that specialize in sectors with high relatedness or high risk, focus is not as negatively related to size. Resource reallocation, therefore, still plays a key role in investment decisions. We can see, though, that it is not the dominant effect. While we might conclude that the bargaining effect reviewed in Section II.1.b dominates the reallocation ability and spurs our results, the high magnitude of the negative
relationship between focus and fund in the entire dataset makes this an unlikely explanation. In fact, Fulghieri and Sevilir’s model (2009) predicts the exact opposite, and Inderst et al. (2007) claim that a “competition effect” counteracts any bargaining effect.
IV. Alternative Hypothesis

IV.1 Explanation of Network Position

Before we present our alternative hypothesis explaining the empirical results from Section III, we must first discuss the concept of a syndication network in venture capital. Syndication refers to the practice of a lead venture capital firm inviting others to co-invest on a deal, thus splitting the total investment and resulting equity shares across venture capital firms. Hochberg et al. (2007) calculate syndication network measures for venture capital firms based mostly on the number of syndicated deals a firm has participated in, whether the firm served as the lead investor on those deals, and how many other VC firms were on each of the deals. The higher the measure, the better “network position” the firm enjoys. Their study concludes that a higher network position at the time of a fund’s vintage year causes higher rates of performance for the fund over its lifetime, as measured by the percentage of the fund’s portfolio companies that are acquired or exited via initial public offerings. The paper states that this boost to performance occurs because a better network position increases a fund’s ability to source high-quality deal flow, as well as to add value to its investments.

Hochberg et al. provide three reasons why network positioning might improve deal flow. First, venture capitalists often invite other firms to co-invest in their promising deals with the expectation that these firms will reciprocate with later deal flow. Additionally, observing each others’ willingness to invest in certain deals allows VC to select investments with more confidence. Lastly, syndication spurs the exchange of information between VCs with different sectors of specialization; this last point implies that a VC can invest across sectors and still reach a higher efficiency of reallocation of assets if she receives advice from those in her network.
IV.2 Deal Flow in Venture Capital: Why Portfolio Focus May Restrict Size

Fulghieri and Sevilir (2009), as support for their conclusion that higher concentration leads to portfolio expansion, claim that a firm’s increased ability to reallocate resources across startups in a focused portfolio dominates the fact that in a concentrated portfolio, an entrepreneur tends to give up bargaining share and, hence, exert less effort. (Section II.1.b). Given our results that portfolio relatedness is highly negatively correlated with size, we might be content to conclude that their model simply led us to the wrong conclusions. However, considering the magnitude and statistical significance of our results, we predict that there must be another mechanism at work in the determination of portfolio size. If the issue were merely a question of domination of the bargaining vs. reallocation effects, with each dominating in different environments, we would not expect such a strong effect for the entire dataset as a whole. Our empirical results also indicate that the resource reallocation effect, while not dominant, is a present factor in determining portfolio size in the presence of focus.

Here, we present a model in which we examine the effects deal flow in a sector might have on portfolio size. Intuitively, one might expect a hierarchy of deals in an industry or sector, in which some deals are better than others. Fulghieri and Sevilir explicitly ignore this facet, assuming that “VCs have access to a large supply of entrepreneurs.” If a venture capitalist desires to invest in a large portfolio of startups and intends to concentrate in one industry, she may find that at some point, investing further in that industry forces her to take on a negative-NPV project. That is, there may be no “good” deals left in the industry (to which she has access). We analyze our main empirical results in light of this hypothesis. That is, we attempt to ascertain the effect decreased deal flow due to specialization has on portfolio size, and we examine how being well-networked among other venture capital firms affects the outcome. In keeping with our
treatment (see Introduction) that venture capital funds’ decisions on specialization are based on
long-term strategy and are much less sensitive to outside parameters than their decisions on size,
we look at the decision processes of generalist firms separately from those of focused firms.
(Hochberg et al. 2008)

Case 1: Generalist Fund

The generalist fund requires simpler analysis. Consider a venture capitalist who does not
place particular importance on concentrating in any one industry, and has a low (but positive)
ability to reallocate assets across her startups with efficiency $\phi$. She has decided to invest in one
startup, because she has not seen many positive-NPV deals. The potential payoff to that startup
equals $2\Delta$, and the VC and entrepreneur will realize that total payoff with probability $p_1$. We
ignore the bargaining effect in order to focus our attention on the deal flow aspect of the model,
and assume that the VC extracts the entire payoff. Thus, the VC’s expected gain equals:

$$\pi_{VC}^1 = 2p_1\Delta$$  \hspace{1cm} (1)

Now, consider that the VC has spent time networking and has suddenly increased her network
position among her peers (of course, building this network in reality takes many years). Her deal
flow increases, and she receives the opportunity to invest in a deal whose probability of success
is defined as $p_2$. If she participates in the second deal, her expected gain equals:

$$\pi_{VC}^2 = 2p_1p_2\Delta + p_1(1-p_2)\Delta(1+\phi) + p_2(1-p_1)\Delta(1+\phi)$$  \hspace{1cm} (2)

She decides to expand her portfolio if $\pi_{VC}^2 \geq \pi_{VC}^1$, or more explicitly, if:

$$p_2 \geq \frac{p_1 - p_1\phi}{\phi(1-2p_1) + 1}$$  \hspace{1cm} (3)
Note that $p_2$ and $\phi$ must be high enough relative to $p_1$. The right-hand side is increasing in $p_1$ and decreasing in $\phi$. We have already stated that the reallocation benefits are very low for the generalist, so if we set $\phi=0$, we see that $p_2$ must exceed $p_1$. The quality of the new deal must exceed that of the initial deal to persuade the VC to expand. Thus, the main driver of expansion is the difference between startup qualities, or $|p_1 - p_2|$. Since the VC is likely to find such a high-quality deal in an unsaturated sector, she likely remains generalist. As the VC’s network position improves and she has greater access to better deals, she has higher incentives to expand. Her decision to expand is based upon her access to deal flow, and also her ability to reallocate resources from failed startups.

**Case 2: Focused Fund**

Now, we consider a fund whose parent firm considers itself a specialist in a certain sector, $S_1$. Our analysis remains similar to that in the general case, except for two differences. One is that the quality of the second deal is constrained to be lower than that of the first, because the VC has already invested in the best deal in her area of specialty. This tells us that $p_1 > p_2$. Secondly, the reallocation parameter, $\phi$, is now much higher because the VC has experience in redeploying resources across startups in this sector.

$$p_2 \geq \frac{p_1 - p_1 \phi}{\phi(1 - 2p_1) + 1}$$

We can see that she may still decide to expand, but her ability to reshuffle resources must be sufficiently high, and the second-best deal in her industry cannot be too much worse than her initial investment. Our empirical results, indicating that focused funds choose to remain smaller, imply that there may be a sharp drop-off in investment quality at some threshold of investment within an industry. As in the generalist fund case, a VC with a greater network position faces a
higher probability that the second-best deal to which she has access is almost as high-quality as the best deal.
V. Final Econometric Model

In order to empirically test our alternative hypothesis, we add network position as a firm fixed effect to our previous model. To our list of firm fixed effects variables in Section III.2, we add the following.

**Firm_Eigenvector**
A measure of closeness in venture capital networks. It takes into account not only the number of syndication ties that a firm has, but also the “quality.” Specifically, it recursively weights a firm’s syndication network by how well-networked each of the ties is. Measures firm’s network position for 5 years prior to fund’s vintage year.

**Firm_Indegree**
A measure of the frequency with which a VC firm is invited to co-invest in other venture capitalists’ deals, thereby expanding its investment opportunity set and gaining access to resources and information. A strong proxy for “deal flow.” Measures firm’s network position for 5 years prior to fund’s vintage year. (Hochberg *et al.* 2007)

**%_Syndication_Curr**
Percent of deals in which a fund engages that are syndicated.

**%_Syndicated_Prev**
Percent of deals in which the firm’s previous fund engage that are syndicated.

**First_Fund**
Binary variable that equals 1 if a fund is its parent firm’s first fund.

We estimate the following model, noting important results in Table V.1.

\[
Fund\_Companies = \beta_1 Concentration_{ijk} + [\beta_2 \ldots \beta_5] Stage\_dummies_{ijk} + \\
\beta_6 Fund\_AUM + [\beta_7 \ldots \beta_{41}] Industry \times Time\_Dummies_{ijk} + \\
\alpha_1 Experience_i + \alpha_2 Capital\_Inflows_k + \alpha_3 Firm\_Eigenvector_j + \alpha_4 Corporate\_VC_j
\]

Note that, in order to incorporate the network position into the model, we must remove all funds whose vintage years are before 1980; this is because the network measures are calculated from investments made during the five years prior to the fund’s vintage year, and our dataset begins with investments made in 1975.
We concentrate our analysis on the Firm_Eigenvector measure of network position; Hochberg et al. (2007) explain that this variable emphasizes the quality of network ties and, potentially, the quality of resulting deal flow. We confirm our results using Firm_Indegree, a network position measure that we use as a proxy for deal flow quantity.
**Table V.1a Using Eigenvector Network Measure**

Explanation of Fund Portfolio Size for Each Measurement of Concentration  
Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-18.73***</td>
<td>-19.92***</td>
<td>-42.59***</td>
</tr>
<tr>
<td></td>
<td>(2.980)</td>
<td>(2.176)</td>
<td>(5.111)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00001530</td>
<td>0.00001120</td>
<td>0.00001270</td>
</tr>
<tr>
<td></td>
<td>(0.00001840)</td>
<td>(0.00001840)</td>
<td>(0.00001770)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>-1.026</td>
<td>-2.178*</td>
<td>-1.477</td>
</tr>
<tr>
<td></td>
<td>(1.324)</td>
<td>(1.296)</td>
<td>(1.252)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03373***</td>
<td>0.03206***</td>
<td>0.03354***</td>
</tr>
<tr>
<td></td>
<td>(0.004759)</td>
<td>(0.004513)</td>
<td>(0.004906)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.0003108***</td>
<td>-0.0004319***</td>
<td>-0.0003481***</td>
</tr>
<tr>
<td></td>
<td>(0.0001093)</td>
<td>(0.0001072)</td>
<td>(0.0001071)</td>
</tr>
<tr>
<td>Firm_Eigenvector</td>
<td>0.6083***</td>
<td>0.5883***</td>
<td>0.6210***</td>
</tr>
<tr>
<td></td>
<td>(0.1038)</td>
<td>(0.1025)</td>
<td>(0.0985)</td>
</tr>
</tbody>
</table>

R^2  
- 25.97%  
- 28.14%  
- 28.11%

All funds who vintage year <1980 are removed; dataset contains 2,006 funds  
* Significant at 10% ** Significant at 5% *** Significant at 1%  
Robust standard errors calculated

**Table V.1b**

Marginal Effects of Main Variables on Fund Portfolio Size  
Standardized Coefficients

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-3.010</td>
<td>-3.588</td>
<td>-4.902</td>
</tr>
<tr>
<td></td>
<td>(0.1607)</td>
<td>(0.1801)</td>
<td>(0.1151)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.5037</td>
<td>0.3687</td>
<td>0.4181</td>
</tr>
<tr>
<td></td>
<td>(32,920)</td>
<td>(32,920)</td>
<td>(32,920)</td>
</tr>
<tr>
<td>Firm_Eigenvector</td>
<td>3.487</td>
<td>3.372</td>
<td>3.560</td>
</tr>
<tr>
<td></td>
<td>(5.732)</td>
<td>(5.732)</td>
<td>(5.732)</td>
</tr>
</tbody>
</table>

Standardized coefficients computed by multiplying OLS coefficients above with independent variable std. deviations  
Numbers in parentheses are independent variable standard deviations
### Table V.2a Using Indegree Network Measure

Explanation of Fund Portfolio Size for Each Measurement of Concentration
Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-18.38***</td>
<td>-20.28***</td>
<td>-41.34***</td>
</tr>
<tr>
<td></td>
<td>(2.998)</td>
<td>(2.173)</td>
<td>(4.991)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.0000003500</td>
<td>-0.000005480</td>
<td>-0.000000777</td>
</tr>
<tr>
<td></td>
<td>(0.00001840)</td>
<td>(0.00001820)</td>
<td>(0.00001790)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>-0.9308</td>
<td>-2.044</td>
<td>-1.405</td>
</tr>
<tr>
<td></td>
<td>(1.332)</td>
<td>(1.503)</td>
<td>(1.264)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03430***</td>
<td>0.03253***</td>
<td>0.03417***</td>
</tr>
<tr>
<td></td>
<td>(0.004772)</td>
<td>(0.004501)</td>
<td>(0.004924)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.0002695**</td>
<td>-0.0003854***</td>
<td>-0.0003089***</td>
</tr>
<tr>
<td></td>
<td>(0.0001093)</td>
<td>(0.0001078)</td>
<td>(0.0001080)</td>
</tr>
<tr>
<td>Firm_Indegree</td>
<td>2.318***</td>
<td>2.312***</td>
<td>2.305***</td>
</tr>
<tr>
<td></td>
<td>(0.4565)</td>
<td>(0.4470)</td>
<td>(0.4478)</td>
</tr>
</tbody>
</table>

R^2                       | 26.80%    | 29.12%    | 28.79% |

All funds who vintage year <1980 are removed; dataset contains 2,006 funds

*Significant at 10%  **Significant at 5%  ***Significant at 1%
Robust standard errors calculated

### Table V.2b

Marginal Effects of Main Variables on Fund Portfolio Size
Standardized Coefficients

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-2.954</td>
<td>-3.652</td>
<td>-4.758</td>
</tr>
<tr>
<td></td>
<td>(0.1607)</td>
<td>(0.1801)</td>
<td>(0.1151)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.01152</td>
<td>0.1804</td>
<td>0.02558</td>
</tr>
<tr>
<td></td>
<td>(32.920)</td>
<td>(32.920)</td>
<td>(32.920)</td>
</tr>
<tr>
<td>Firm_Indegree</td>
<td>13.48</td>
<td>13.44</td>
<td>13.40</td>
</tr>
<tr>
<td></td>
<td>(5.815)</td>
<td>(5.815)</td>
<td>(5.815)</td>
</tr>
</tbody>
</table>

Standardized coefficients computed by multiplying OLS coefficients above with independent variable std. deviations
We see that both measures of network position have a significantly positive effect on portfolio size, which provides evidence that increased deal flow does, indeed, result in portfolio expansion. In particular, a fund whose parent firm enjoys an eigenvector network position one standard deviation higher than the average firm invests in over three more companies than the average fund. Even more strongly, a fund whose parent firm enjoys an indegree network position one standard deviation higher than the average firm invests in over thirteen more companies than the average fund. Including network position in the model increases its R^2 by almost three percent across all three measures of concentration. When we include network position in our regressions, firm experience loses significance, indicating that a firm’s experience may be tied closely to its network position. We might expect this result, since having made more investments gives a firm a chance to have made more syndicated investments. However, it points to the possibility that firm experience does not affect portfolio size through improved efficiency in reallocating assets, but rather through superior deal flow.

Robustness of Results

In order to ensure that the impact of network position on fund size is not simply being driven by a tendency for a particular firm to syndicate many deals, we control for the percent of deals the current fund, and the firm’s previous fund, have syndicated. These results do not significantly impact our regression, and we include them in Appendix A (Tables A.1 and A.2). Additionally, we cluster by firm and year to correct for correlation across firms and years. Clustering does not significantly alter our estimates. (Appendix A, Tables A.3 and A.4)
VI. Additional Explanations

VI.1 Portfolio Size as a Signal: Reputation Serves as an Incentive

Venture capital funds do not necessarily always have their choice of unlimited startups; rather, they sometimes compete to invest in high-quality startups. For VC funds that find themselves in this situation, it may be the case that reputation in their markets is more important than in the usual cost-benefit analysis. For instance, all models reviewed thus far have ignored the fact that, empirically, entrepreneurs prefer to work with VC firms that possess specialized knowledge of their startups’ production processes and competitive landscapes. (Hochberg et al. 2008) A fund may find it necessary to remain small in order to signal to future entrepreneurs, in either the current fund or one of the fund’s future funds, that the fund will not utilize its bargaining power to exploit entrepreneurs.

The models reviewed here tell us that the VC’s incentives to exploit entrepreneurs during bargaining are highest when her portfolio focus is high, because she can reallocate resources efficiently. Despite whether a VC is type Friendly (F) or Greedy (G), an entrepreneur always has reason to be suspicious when he is negotiating with a VC who has a large and focused portfolio. Since he knows that being denied refinancing in the future will hurt his startup much more than choosing a suboptimal VC in the present, he will choose to go elsewhere. Because it is costly for a small VC of type G (Greedy) to use her focus to exploit entrepreneurs during the bargaining process (in terms of foregone payoff, because entrepreneurial effort is more necessary when the payoff per project is higher), she can prove that she is of type F (Friendly) by remaining small.
VI.2 Venture Capital Risk Aversion

All models presented thus far assume that venture capitalists are risk-neutral and base their decisions solely on the expected values of outcomes. Sahlman (1990) reports that between 1965 and 1985, only about two thirds of venture capital investments resulted in absolute gains. Approximately one in fifteen investments resulted in returns that were ten times or more the VC’s investment. These statistics show the high level of uncertainty with which venture capitalists deal, and the necessity for them to manage this risk.

Norton and Tenenbaum (1993) discuss two ways in which a venture capitalist can manage the risk of her investments. Under the assumptions of the Capital Asset Pricing Model, capital markets reward investors for systematic risk and assume that unsystematic risk is diversified away. For this reason, a venture capitalist might choose to diversify her risk across sectors and companies. However, the authors note that the venture capital market is rife with exceptions to the CAPM assumptions; agents are faced with asymmetric information, there certainly are transactions costs, and expectations have a heterogeneous set of expectations. It may be that firm specialization mitigates risk more effectively than diversification. Specialization causes a learning curve effect, according to Sahlman (1990), allows a firm to share information among other specialists, and provides a firm with a reputation of being an expert in a particular sector.

If Norton and Tenenbaum are correct, and specialization in a particular sector does lower risk from investing in that sector, a highly focused fund does not need to invest in a large portfolio in order to reach target risk levels. If total portfolio risk is an important driver in investment choices, we might expect this effect to contribute to the negative relationship between fund focus and portfolio size.
VII. Conclusion

In this paper, we examine the determinants of the optimal number of companies in a venture capital fund’s portfolio, based on opposing incentives and agency costs. Specifically, we analyze how a portfolio’s size varies with its sector concentration (by industry, geography, and developmental stage), an important question given that many venture capital firms brand themselves as “specialists” in order to differentiate themselves from competitors.

First, we review past literature and models to identify the main drivers of incentives in venture capital portfolio size decisions. The “value dilution effect” occurs because venture capital funds’ resources, in terms of human and financial capital, are scarce. Investing in a larger number of companies requires that a VC fund spread its advice and resources across its investments. (Kanniainen and Keuschnigg 2003) Competition between a larger number of portfolio companies for limited resources, as well as the risk to each entrepreneur that the VC will discontinue his project in favor of other projects, results in a “bargaining effect”: lower effort on the part of an entrepreneur due to a lower post-bargaining share of his project’s payoff. (Bernile et al. 2007) An improved ability to reallocate resources from failed startups to successful ones in a large portfolio leads to a “redeployment effect” for VCs; they are more willing to invest in more companies when they can recover resources from failed investments. Higher sector concentration augments the ability to reallocate resources across startups. (Fulghieri and Sevilir 2009)

We hypothesize from our review of past studies that portfolio focus and size are positively related, because the resource reallocation effect dominates the other effects mentioned above for focused portfolios. Furthermore, we expect that funds focused in sectors that allow for even greater redeployment of resources exhibit a more strongly positive relationship between
size and focus. Higher-quality firms should also invest in larger portfolios because they are more adept at reshuffling resources across startups.

We find that, empirically, more focused funds invest in smaller portfolios. The magnitude of this effect is smaller in funds that specialize in areas with high risk or high relatedness among startups, suggesting that the reallocation effect, while not dominant, is still certainly present in portfolio size decisions. Firm experience significantly increases portfolio size until we control for firm network position, which tells us that firm quality affects the size of a fund through a mechanism (discussed below) other than the reallocation effect.

Next, we introduce an alternate hypothesis regarding the relationship between optimal portfolio size and concentration, demonstrating that the deal flow to which a VC has access helps to determine her incentives to invest in a larger portfolio. This hypothesis hinges on the assumption that a VC constrained to focus in a particular sector is faced with a smaller number of positive-NPV deals.

We test this hypothesis by including in our previous econometric model the network position of a fund’s parent firm at the time the fund’s capital is raised. Hochberg et al. (2007) argue that a higher network position allows a firm to enjoy higher deal flow. We find, in support of our alternate hypothesis, that a better network position (and, thus, higher quality deal flow) leads a venture capitalist to choose a larger portfolio.

Our results open doors for both theoretical and empirical future research. We propose several additional explanations that might serve to explain our empirical results that more focused firms generally choose to stay smaller. First, VC firms may exhibit a degree of selection bias; a venture capital firm that chooses to specialize in a certain sector may be focused in a capital market that either highly values the reputation of a VC firm, or requires high incentives to
exert effort on the part of entrepreneurs. These VC firms may need to signal to entrepreneurs using their portfolio sizes that they will not exploit them at later refinancing stages. Secondly, all models reviewed have assumed that VCs are risk-neutral, which is realistically not the case. We claim that venture capitalists who normally choose large portfolios in order to diversify risk across startups can mitigate risk in other ways due to the information asymmetries inherent in the VC capital markets. Specifically, they can mitigate risk by focusing more in a particular sector, facilitating information exchange and specialized knowledge. This allows them to lower risk to designated risk targets by focusing, in place of diversifying. Lastly, the average fund in our dataset syndicates approximately 74% of its deals. Syndication of investments serves a crucial role in venture capital decision-making; however, we do not build this practice into the theoretical models presented in this paper. Further research may examine how the syndication of deals affects venture capital portfolio size choices.
VIII. References


## IX. Appendix A

### Table A.1

<table>
<thead>
<tr>
<th>Concentration Measure by:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-18.08***</td>
<td>-20.55***</td>
<td>-45.62***</td>
</tr>
<tr>
<td></td>
<td>(2.993)</td>
<td>(2.128)</td>
<td>(4.923)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00001760</td>
<td>0.00001350</td>
<td>0.00001540</td>
</tr>
<tr>
<td></td>
<td>(0.00001880)</td>
<td>(0.00001880)</td>
<td>(0.00001810)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>-0.9202</td>
<td>-2.291*</td>
<td>-1.512</td>
</tr>
<tr>
<td></td>
<td>(1.323)</td>
<td>(1.288)</td>
<td>(1.235)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03298***</td>
<td>0.03112***</td>
<td>0.03239***</td>
</tr>
<tr>
<td></td>
<td>(0.004667)</td>
<td>(0.004401)</td>
<td>(0.004755)</td>
</tr>
<tr>
<td>L_Ind_Weighted_Inflows</td>
<td>-0.0003204***</td>
<td>-0.0004357***</td>
<td>-0.0003450***</td>
</tr>
<tr>
<td></td>
<td>(0.0001089)</td>
<td>(0.0001070)</td>
<td>(0.0001061)</td>
</tr>
<tr>
<td>%_Syndication_Curr</td>
<td>-5.451**</td>
<td>-6.458***</td>
<td>-8.005***</td>
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<tr>
<td></td>
<td>(2.212)</td>
<td>(2.172)</td>
<td>(2.176)</td>
</tr>
<tr>
<td>Firm_Eigenvector</td>
<td>0.6331***</td>
<td>0.6164***</td>
<td>0.6588***</td>
</tr>
<tr>
<td></td>
<td>(0.1063)</td>
<td>(0.1048)</td>
<td>(0.1005)</td>
</tr>
</tbody>
</table>

R^2: 26.20%, 28.29%, 28.46%

All funds who vintage year <1980 are removed; dataset contains 2,006 funds

* Significant at 10%  ** Significant at 5%  *** Significant at 1%

Robust standard errors calculated
## Table A.2

Explanation of Fund Portfolio Size for Each Measurement of Concentration Controlling for Previous Fund Syndication %: Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-26.00***</td>
<td>-22.19***</td>
<td>-45.12***</td>
</tr>
<tr>
<td></td>
<td>(4.027)</td>
<td>(2.904)</td>
<td>(6.710)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00002650</td>
<td>0.00002070</td>
<td>0.00002500</td>
</tr>
<tr>
<td></td>
<td>(0.00001900)</td>
<td>(0.00001900)</td>
<td>(0.00001800)</td>
</tr>
<tr>
<td>Corporate_VC</td>
<td>2.908</td>
<td>-2.209</td>
<td>1.816</td>
</tr>
<tr>
<td></td>
<td>(2.874)</td>
<td>(2.752)</td>
<td>(2.644)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03082***</td>
<td>0.02943***</td>
<td>0.03060***</td>
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<tr>
<td></td>
<td>(0.003772)</td>
<td>(0.003608)</td>
<td>(0.003943)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.0001371***</td>
<td>-0.0002803**</td>
<td>-0.0002106*</td>
</tr>
<tr>
<td></td>
<td>(0.0001399)</td>
<td>(0.0001268)</td>
<td>(0.0001276)</td>
</tr>
<tr>
<td>%_Syndication_Prev</td>
<td>3.006</td>
<td>2.621</td>
<td>1.345</td>
</tr>
<tr>
<td></td>
<td>(2.187)</td>
<td>(2.169)</td>
<td>(2.152)</td>
</tr>
<tr>
<td>Firm_Eigenvector</td>
<td>0.6012***</td>
<td>0.5995***</td>
<td>0.6201***</td>
</tr>
<tr>
<td></td>
<td>(0.1247)</td>
<td>(0.1236)</td>
<td>(0.1187)</td>
</tr>
<tr>
<td>R^2</td>
<td>25.97%</td>
<td>32.82%</td>
<td>33.18%</td>
</tr>
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</table>

All funds who vintage year <1980 are removed; dataset contains 2,006 funds

* Significant at 10%  ** Significant at 5%  *** Significant at 1%

Robust standard errors calculated
### Table A.3

**Explanation of Fund Portfolio Size for Each Measurement of Concentration**

Clustering by Firm: Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th>Concentration Measure By:</th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>-18.73***</td>
<td>-19.92***</td>
<td>-42.59***</td>
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<tr>
<td></td>
<td>(3.443)</td>
<td>(2.372)</td>
<td>(5.525)</td>
</tr>
<tr>
<td>Experience_Weighted</td>
<td>0.00001530</td>
<td>0.00001120</td>
<td>0.00001270</td>
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<td></td>
<td>(0.00002250)</td>
<td>(0.00002270)</td>
<td>(0.00002070)</td>
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<tr>
<td>Corporate_VC</td>
<td>-1.026</td>
<td>-2.178*</td>
<td>-1.477</td>
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<tr>
<td></td>
<td>(1.425)</td>
<td>(1.425)</td>
<td>(1.337)</td>
</tr>
<tr>
<td>Fund_AUM</td>
<td>0.03373***</td>
<td>0.03206***</td>
<td>0.03854***</td>
</tr>
<tr>
<td></td>
<td>(0.004236)</td>
<td>(0.004007)</td>
<td>(0.004341)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
<td>-0.0003108***</td>
<td>-0.0004319***</td>
<td>-0.0003481***</td>
</tr>
<tr>
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<td>(0.0001144)</td>
<td>(0.0001118)</td>
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<td>Firm_Eigenvector</td>
<td>0.6083***</td>
<td>0.5883***</td>
<td>0.6210***</td>
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<tr>
<td></td>
<td>(0.1155)</td>
<td>(0.1180)</td>
<td>(0.1066)</td>
</tr>
</tbody>
</table>

| R^2                       | 25.97%   | 28.14%    | 28.11%  |

All funds who vintage year <1980 are removed; dataset contains 2,006 funds

* Significant at 10%  ** Significant at 5%  *** Significant at 1%
Robust standard errors calculated
### Table A.4

**Explanation of Fund Portfolio Size for Each Measurement of Concentration**

Clustering by Year: Firm and Year Fixed Effects

<table>
<thead>
<tr>
<th></th>
<th>Industry</th>
<th>Geography</th>
<th>Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
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<td>(4.341)</td>
<td>(3.086)</td>
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<td>(0.00005020)</td>
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</tr>
<tr>
<td>Corporate_VC</td>
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<td>-2.178</td>
<td>-1.477</td>
</tr>
<tr>
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<td>(2.082)</td>
<td>(2.012)</td>
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<tr>
<td>Fund_AUM</td>
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<td>0.03206***</td>
<td>0.03854***</td>
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<td>(0.004757)</td>
<td>(0.005145)</td>
</tr>
<tr>
<td>L_Ind_Weighted Inflows</td>
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<td>-0.0004319***</td>
<td>-0.0003481***</td>
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<td>(0.0000887)</td>
</tr>
<tr>
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<td>0.5883***</td>
<td>0.6210***</td>
</tr>
<tr>
<td></td>
<td>(0.1581)</td>
<td>(0.1583)</td>
<td>(0.1399)</td>
</tr>
</tbody>
</table>

R\(^2\)                       | 25.97%      | 28.14%      | 28.11%       

*All funds who vintage year <1980 are removed; dataset contains 2,006 funds*

*Significant at 10%  **Significant at 5%  ***Significant at 1%  
Robust standard errors calculated